CHAPTER 2

LITERATURE REVIEW

This chapter presents a review of the most widely cited and recent approaches that involve wavelet based adaptive filtering and speckle removal.

2.1 SPATIAL DOMAIN FILTERS

Lee filter, developed by Lee (1980), is an adaptive filter. The characteristic of the filter is adapted based on the local statistics estimated using the neighbourhood of a pixel. Lee filter has the ability to remove noise present in flat regions, while leaving the fine details like textures and lines unaltered, Hence noise is still present in the areas of textures and lines. This is the major limitation of this filter as mentioned by Bhoi (2009).

Kuan Filter (Kuan et al 1987) is developed to remove noise existing in images while keeping the edge features. This is achieved by transforming the multiplicative model of noise into a signal dependent additive model. Noise if filtered using Minimum Mean Square Error (MMSE) criterion. The function of Kuan filter resembles Lee filter, except in the weighting function. The limitation of this filter is its dependency on ENL measure from an image to determine the weight factor.

Frost filter developed by Frost et al (1982) assumed a multiplicative noise model for the speckle. Filtering is achieved by replacing the noisy pixel with a weighted sum of the pixel values considered inside a moving window of size nxn. Frost filter maintains a balance between all-pass and averaging filter. It performs similar to mean filter but with less noise suppression.

2.2 WAVELET DOMAIN FILTERS

Multi-scale wavelet transform is effectively applied in image denoising for suppressing speckle in ultrasound imaging, owing to its various advantages. The ability of wavelet transform to represent an image at several resolution scales gives more accurate information about the features of interest and noise. The noise removal filters developed using wavelet transform can be broadly divided into two types, homomorphic wavelet filtering and nonhomomorphic wavelet filtering techniques (Gupta et al 2005). The homomorphic technique first performs logarithmic transformation of the image. Filtering is done following which an exponential transformation is carried out. (Zong et al 1998, Achim 2003, Gupta et al 2004 and Michailovich & Tannenbaum 2006). On the other hand, the non homomorphic approaches perform filtering of the wavelet subband coefficients of the speckle corrupted image as investigated by Pizurica et al (2003) and Gupta et al (2004). However, the homomorphic wavelet filtering approaches bear two major shortcomings. First, as the logarithmic transform is nonlinear in nature, it alters the mean value of homogeneous pixels, leading to the biased estimation of reflectivity. Secondly, performing logarithmic and exponential transformations makes the approach computationally expensive. To overcome these shortcomings, non homomorphic approaches (Pizurica et al 2003 and Yue et al 2006) have been analyzed that filtered the wavelet coefficients of the speckle corrupted image, without taking log and exponential transformations.

The goal of wavelet denoising is to eliminate noise present in images and to retain the important image characteristics. Wavelet shrinkage techniques applied on noisy images involve the following operations:

- taking a forward wavelet transform
- application of a suitable thresholding function to shrink the wavelet coefficients based on a suitable threshold
- reconstructing the original image by taking inverse wavelet transform

The performance wavelet shrinkage approach relies heavily on the selection of threshold and the thresholding rule. Based on the study about various wavelet based denoising filters from the literature for the past two decades, it is seen that the research directions of wavelet based denoising focuses on the following:

- selection of wavelet transform
- determination of adaptive threshold
- development of new thresholding functions and
- multiscale product based methods

2.2.1 Development of Thresholding Functions

Wavelet shrinkage is based on a policy of modifying the wavelet coefficients using a rule in the wavelet domain (Donoho 1995). Thresholding functions define a rule, whether to keep or remove a wavelet coefficient. Various thresholding functions have been introduced in the literature to enhance the efficiency of speckle suppression filters. The well known wavelet thresholding functions are (i) hard thresholding and (ii) soft thresholding. The shortcomings of these rules are, hard thresholding shows discontinuity at the thresholds and soft thresholding introduces fixed bias. Other thresholding functions like semi soft by Gao & Bruce (1997), non-negative garrotte by Gao (1998) were studied in the denoising literature. These two thresholding functions, garrotte and semisoft shrinkage functions were developed in such a way as to give a compromising performance of soft and hard shrinkage functions. The limitations of these thresholding functions are their fixed nature, lack of higher order differentiability and they rely on the value of threshold. These limitations tend to reduce the functionality and flexibility of the algorithms. Therefore, new classes of shrinkage functions have been developed by the researchers with different shape tuning factors.

Qin et al (2010) scheduled a new denoising algorithm for digital images using wavelets via a new thresholding function. The new thresholding function has two advantages. It avoids the phenomena of Gibb's shock exhibited by hard thresholding function and also reduces the fixed bias exhibited by the soft thresholding approach. A weighted rule is adopted to estimate the noise free coefficients. This method was adopted for the removal of Gaussian noise. Incorporation of correlation of wavelet coefficients and implementation in the spatial adaptive case are recommended for further improving the efficiency of the algorithm.

Andria et al (2013) presented a new thresholding procedure to suppress speckle noise existing in US images. It used an adaptive data-driven exponential operator to shrink the wavelet coefficients of the US image. The parametric approach adapted the thresholding parameters to the wavelet level decomposition and reduced the coefficients around the zero zone gradually to zero. The parameters for threshold are to be determined empirically through several simulation tests. Therefore, computation involved is high.

From the above literatures it is seen that the gradual decay of the coefficients resulted in a more appropriate reconstruction. However the utilization of secondary wavelet properties for noise reduction and the empirical determination of parameters limited the performance of the thresholding functions. These short comings are overcome in the proposed thresholding functions in SIIAWF and ISTWF discussed in chapter 4 and chapter 5.

2.2.2 Adaptive Threshold Determination

Several research studies have been carried out extensively on wavelet thresholding for the removal of noise in digital images, owing to the efficacy and simplicity of wavelets. To a large extent, focus towards the selection of an optimal uniform threshold has been concentrated. Only a few research studies have been carried out to develop an adaptive threshold, according to the local statistics of the coefficients. Introduction of such local statistics (like information about smooth regions and edges) tends to improve the performance of wavelet shrinkage algorithm. The following are some of the studies in this focus.

Chang & Vetterli (1997) devised a spatially adaptive wavelet thresholding for image denoising. The algorithm proposed a method to improve the uniform threshold with the spatial changing characteristics of the regions like edges, texture and smooth regions. This was achieved by first segmenting the image into different regions. The thresholds for each of the regions are used to perform soft thresholding. The performance of the approach seemed to be improved, but the complexity grew up as segmentation of several regions was involved. So a systematic way of threshold determination is suggested for further improvement.

Chang et al (2000a) improvised a spatially adaptive wavelet thresholding method based on context modelling used in image compression experiments. Here each subband coefficient was modelled as a random variable assuming a generalized gaussian prior through unknown parameters. The parameters were estimated using context modelling for each coefficient, which was used for adapting the threshold. Thus, this method of selection of threshold using the local characteristics of the coefficients aided in retaining the edge and texture details. The computation involved in the calculation of weight was high and complex. Also the context considered the coefficients that were not spatially adjacent.

Chang et al (2000b) mooted an adaptive data-driven threshold for noise removal in digital images. Soft thresholding was utilized for shrinking the noisy coefficients. The estimated threshold was subband adaptive and was derived considering a Bayesian framework. It was a data driven threshold, as the estimates of the parameters for the threshold were done from the coefficients of each subband. The performance was found to be better and may be further improved by incorporating spatial adaptivity to the threshold estimated. The calculation of weight parameter involved matrix operations, which increased the computational time complexity.

Mihcak et al (2004) presented a simple spatially adaptive statistical model for wavelet coefficients for image denoising. In this approach, Maximum Likelihood (ML) or Maximum-A-Posteriori (MAP) estimation was utilized to evaluate the signal variance around a local neighbourhood. The size and shape of the window was fixed in this approach. Modifications on these, would improve the performance of the denoising algorithm.

Eom & Kim (2004) adopted a new algorithm for the estimation of signal variance by varying the size of the locally adaptive window. It was done using a region-based approach. A region around the denoising point was divided into disjoint sub regions. The locally adaptive window was obtained by selecting the proper sub regions, based on a homogeneity measure. The algorithm proved to be efficient when applied on Gaussian noise corrupted images. The derived measure considered the sub regions rather than each coefficient and not their inter and intra scale dependencies.

Sudha et al (2009) investigated a rather simple procedure for the selection of adaptive threshold using context based modelling in the wavelet domain. The threshold adaptation strategy involves computation of weighted variance with suitably selected weights. The noise affected coefficients are thresholded using the product of adjacent subband coefficients. Experimental results showed a better performance compared to VisuShrink and Bayes Shrink.

2.2.3 Multiscale Product and Inter –Intra Scale Dependency Methods

Wavelet transforms are effectively applied for signal and image processing applications mainly based on their multiresolution ability. Wavelet decomposition depicts a signal or image by the power at every scale and position. The correlation of the coefficients within the resolution scale is called intra-scale dependency and across the scale is called as inter-scale dependency. Large magnitude coefficients at coarser scales represent signal of interest and low magnitude coefficients are characterized by noise. The persistence of wavelet coefficients across resolution scales is used for noise removal in a variety of ways as seen from the literature.

Pizurica et al (2001), Pizurica et al (2003) deployed a robust wavelet domain method for noise filtering in medical images. The algorithm performed a preliminary coefficient classification employing the information about the relationship of subband coefficients located at adjacent resolution scales. Using this, the statistical distributions of image and noise coefficients are estimated empirically. A wavelet domain indicator was defined based on the local spatial activity of the coefficients, which were used in adapting the spatial context. The computation involved is high.

Zhang et al (2003) studied an approach for improving restoration of images from their noise corrupted version, utilizing both intra and inter-scale dependencies, existing among the wavelet coefficients. The wavelet coefficients which have the same spatial orientation, at several scales were grouped as a vector. Noise removal was carried out using MMSE estimator. The co-variance matrix of each vector was estimated locally via a square sized window. High computation involved in the determination of covariance matrix of inter-scale coefficients.

Rahman & Hasan (2003) introduced, the iterative center weighted median filter for the removal of noise using wavelet analysis. An improved method of variance estimation was carried out, with the incorporation of both intra and inter-scale dependencies of the decomposed subband coefficients. The estimated variance field is applied in a MMSE estimator to remove noise. High PSNR value could be obtained along with preservation of edge details. The filter is iterative in nature, hence computation involved is high.

Chen et al (2007) introduced an inter-scale, adaptive, data-driven threshold for image denoising via wavelet soft-thresholding. Generalized Gaussian Distribution (GGD) along with the near exponential prior was used in precise modelling of the wavelet coefficients distribution. This method determined an adaptive threshold for each of the subband coefficients. Computational complexity involved is high.

Chen et al (2009) presented a new statistical model for the wavelet coefficients based on their inter-scale dependency to develop an enhanced denoising filtering scheme. The methodology calculated the context as the variance estimation based on a local neighbourhood. Then, MMSE estimator is employed to shrink the noise corrupted wavelet coefficients. The algorithm proved to be computationally competent, and exhibited superior performance in terms of high PSNR and in visual quality. Incorporation of inter-scale dependency is the scope for further improvement.

Dwivedi & Singh (2010) evolved an effective and a simple denoising algorithm making use of the intra-scale and inter-scale dependencies of wavelet coefficients of the power quality signal data. This algorithm performed better time localization and detection of power quality disturbances. It exploited the correlation of multiscale coefficients and the variance of the coefficients was estimated and the MMSE was used for noise removal. Application of undecimated wavelet bases may further improve the performance.

Matsuyama et al (2012) & Tsai et al (2013) put forth a method attempting to reduce noise in mammograms using undecimated wavelet transforms. This algorithm works on the hierarchical correlation of the discrete stationary wavelet transform coefficients. If the correlation value was greater than a threshold then those were signal components and were retained; otherwise they were treated as noise components and were made zero. The modified UDWT performs decomposition of the input image upto two levels only and hence the computation time was reduced. The threshold used was universal threshold, not an adaptive threshold.

The literatures discussed in sections 2.2.2 and 2.2.3 dealt several methods for signal variance estimation through context selection which improved the threshold selection. However they exhibit complex computations or doesnot exploit the correlation of the adjacent scale coefficients and not much importance on preserving the fine details. Also using the multi-scale product for thresholding kills some of the significant details also. Hence, efficient and low complex context based signal variance estimation techniques using the intra and inter-scale dependencies are discussed in SIIAWF for improved adaptive threshold selection and hence for edge preservation.

2.2.4 Fusion Based Denoising

Recently, a lot of interest has been generated for applying image fusion techniques in several areas. Image fusion is a process of extracting information from several sources, with the objective of constructing a single image. It is more informative than the original source images, so that the resulting fused image gives better human and machine interpretation. Since practical imaging sensors introduce noise inherently, it is important to develop an integrated technique of noise removal and fusion of images. In recent years, wavelet based fusion techniques have become popular and proved to be efficient in developing noise free digital images.

Rahman et al (2010) posited a new wavelet domain fusion technique for integrating the noisy source images based on image contrast. Noise from source images is suppressed by extracting the signal and noise dominated coefficients individually, through a comparison of absolute differences of local standard deviation and noise strength. For fusing the coefficients, the magnitude of the denoised coefficients are modified to the maximum if they are signal dominated coefficients and to the minimum if they are noise dominated coefficients, depending on the contrast. The performance of the algorithm degrades when noise level increases.

Vatsa et al (2009) presented an algorithm for medical 3D image denoising and segmentation using Redundant Discrete Wavelet Transform (RDWT). The medical images were denoised using Perona Malik's (Perona & Malik 1990) RDWT based algorithms individually. The two denoised output images are integrated using an entropy based fusion rule. The results suggested that this algorithm provided a better performance than the existing fusion approaches.

Bhutada et al (2011) stipulated an edge preserved adaptive fusion for enhancing the digital images. It used source images denoised through wavelet and curvelet transform. Using wavelet and curvelet transforms, the image was split into homogeneous, non-homogeneous and neither homogeneous nor non-homogeneous regions. The residue obtained from wavelet denoising is again denoised with curvelet, to extract the edge information. This is used for fusing offshore regions of wavelet and curvelet denoised outputs. The proposed fusion technique resulted in an improved preservation of edges. The computational complexity of separating the regions using a thresholding neural network was high.

Swami & Jain (2014) presented an efficient image denoising method that adaptively combined the features of wavelets, wave atoms and curvelets. The noisy image was decomposed into homogeneous and texture parts. Homogeneous region was denoised using wavelet transform and texture region using wave atoms. A variance based fusion is carried out to fuse the denolised outputs. To further improve the performance, edges were located and denoised using curvelet transform. The denoised output resulted in an efficient preservation of edges and textures in the image. The approach utilizes complicated algorithm involving various processing techniques for noisy coefficients.

The fusion based schemes discussed in this section utilize either complex steps for extracting the important image details or combine images processed using different techniques like curvelet and waveatoms. Hence the idea of applying UDWT based wavelet fusion utilizing the intra and inter-scale correlation is proposed in FBWF in chapter 6.

2.3 SUMMARY

Several techniques for suppression of speckle had been reported in the literature for the past two decades. Among those techniques wavelet based approaches have proved to be effective(Donoho1995, Qin et al 2010, Andria et al 2013, Chang et al 2000 a &b, Pizurica et al 2001, Pizurica et al 2003, Chen et al 2007 and Matsuyama et al 2012. Based on the studies UDWT is preferred for image denoising for information preservation. Most of the context based spatial adaptation techniques developed are computationally complex. Hence a simple and efficient approach for determining the adaptive threshold still requires further investigation. Also, the incorporation of the correlation of the coefficients in the determination of parameters of the threshold has not been carried out by many researchers. Most of the thresholding schemes concentrated on modifying coefficients above the threshold and less effort has been made for modifying the low magnitude coefficients. In addition, most of the filters aim at improving the PSNR, thereby producing a smoothed output with less edge preservation. Therefore, a simple and efficient speckle reduction approach with simultaneous preservation of edges is still a vibrant area of research.