Speckle removal in medical ultrasound images by compounding and filtering

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Speckle Removal in Medical Ultrasound Images
By
Compounding and Filtering

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School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
Doctor of Philosophy

2007

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research done by me and has not been submitted for a higher degree to any other University or Institute.

.....

Date

.....

Zhang Lichen

To all members in my family,
for their love and never-ending encouragement.

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Summary

Nowadays, ultrasound imaging has been widely used in medical diagnostics. However, the examination results are greatly affected by the poor ultrasound image qualities due to the existence of speckle noise. This research work focuses on developing efficient speckle reduction methods to increase the quality of ultrasound images.

One commonly used method for enhancing ultrasound images is compounding. Based on the electronic steering technique, a spatial compounding using subapertures divided in a phase array is discussed. The transmit-receive subaperture combination varies at each image construction turn. The images obtained through different active subaperture combinations are partially correlated and averaging these images can suppress speckle. Two classes of subapertures are discussed in the proposed compounding method: non-overlap and overlap. Simulations were carried out using the real ultrasound phantom data and the results show the good ability of the new compounding method on improving ultrasound image qualities.

Recently, image filtering methods for suppressing speckle in ultrasound images received large attentions. Two newly developed approaches of filtering method are presented in the thesis. Both of them have a structure of filtering the Laplacian pyramids (LP) of the original speckle image. The first approach employs the filters

combining a sharpener and a smoother to process each LP layer. To increase the noise reduction results without damaging important features, the sharpener and smoother of the selected filters are adjusted to give a varied performance among different LP layers. The second filtering method is developed for smoothing speckle images with logarithmic compressions, which is often employed by the medical ultrasound scanners to reduce the signal dynamic range. In the second method, the adaptive Dutt filter is employed to smooth the LP layers of the input log-compressed images. At each LP layer, the filter's performance is guided by a speckle statistical parameter, which is derived from the variance of the LP layer regarding to the operations involved in LP generation. Both LP filtering approaches were tested and compared with other speckle filters, using the synthetic data, the real data of a phantom, and *in vivo* data. Visual observations and quantitative measurements show the two approaches suppress speckle effectively without damaging important image features.

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Chapter 1

Introduction

1.1 Medical Ultrasound Imaging Basics

Audio frequency is in the range from 20 Hz to 20 KHz. Sound waves with higher frequencies than 20 KHz are commonly called ultrasound. The frequencies used in medical ultrasound imaging are as high as 1.5 MHz up to 60MHz. When an ultrasound beam is projected into a human body, it travels through the body until striking interfaces between two tissues with different physical properties, such as density or compressibility. At the interfaces, a portion of the ultrasound will be reflected back and the remaining continues traveling until it vanishes due to attenuation. Useful information of tissues within the detection region can be acquired through analyzing the reflected ultrasound echoes, which are collected by ultrasound receivers.

The first use of ultrasound for medical diagnostics can be traced back to the early 1950s. Since then, many researchers took great efforts to advance the technology and apply it into more clinical applications. Nowadays, ultrasound has become a leading medical imaging modality widely used in cardiology, obstetrics and gynecology, abdominal imaging, and vascular imaging. Compared with other technologies, X-Rays, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Positron Emission

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Tomography (PET), it is low cost, fast, and convenient, providing a less harmful but certainly effective method for “in vivo” diagnosis.

Among four scanning modes in ultrasound imaging – amplitude (A-mode), brightness (B-mode), motion (m-mode) and color (C-mode) – B-mode is most frequently used in medical examinations, which allows doctors to see images of the tissue structures under examinations in real time. Fig. 1-1 illustrates the main processing stages to construct a typical B-mode ultrasound image [128], [129]. The ultrasound pulse is generated by converting electrical pulses from a piezoelectric transducer, whose center frequency is always considered as the carrier frequency. The acoustic waves are often focused to improve the lateral resolution and sensitivity. As the acoustic wave travels through the tissues, a portion of energy is reflected back at the tissue interfaces. The echoes are detected by the receiver elements and converted into electrical signals at radio frequency (RF). The RF signals are then amplified with variable gains in proportion to the depth to compensate the energy loss with depth occurred during the wave traveling. This is also referred as time gain compensation (TGC). A so called beamformer is then applied to get the amplified signals electronically focused and steered to form a scan line. The demodulation is performed on the generated scan line to remove the carrier frequency. The envelop signal of the demodulated scan line is then detected. A B-mode image is formed when all envelope signals of the required scan lines are obtained by repeating the above operations. Before display, the logarithmic compression and scan conversion are often employed in medical ultrasound imaging systems. The logarithmic compression reduces the signal dynamic range to match that of a display. It also enhances the contrast in the dark areas. Scan conversion is to reshape the image and map the sampling points at scan lines into the display pixels. Methods for enhancing the B-mode images, if employed,

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are often performed after obtaining echo envelopes. For example, the averaging operations of the compounding methods are usually implemented before the log-compression (Fig. 1-1). And the image filtering methods for reducing speckle are commonly integrated before or after the log-compression (Fig. 1-1). These two kinds of methods can exist simultaneously. All stages above should be processed within a time limit to meet the requirement of real time display. In a modern real time ultrasound scanners, commonly 120 to 300 scan lines are used to construct an image and the frame rate of 5 to 80 images per second can be achieved [128].

Fig. 1- 1 Illustration of operations in B-mode ultrasound imaging

1.2 Research Motivations

As a coherent imaging method, ultrasound imaging always suffers from a kind of noise called as speckle [1]-[6]. It is caused by the interference of energy from randomly distributed scatterers, which are too small to be resolved by the imaging system. Speckle tends to reduce image contrast and detail resolutions. It conceals fine tissue structures and

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increases the difficulty in diagnostic examinations. Hence, speckle removal is often expected to improve qualities of medical ultrasound images.

Many methods have been developed to suppress speckle, which can be mainly classified into two techniques: compounding and filtering [123], [124]. Compounding is a method of averaging several images of the same target with different imaging conditions, among which uncorrelated speckle is considered to be developed [18]-[44]. Compounding is mainly performed on three domains: spatial, frequency and temporal. In spatial compounding, images for averaging are obtained by varying the spatial directions of the array relative to the target, for example, moving the transducer from one place to another. Frequency compounding can be implemented by obtaining images from different acoustic frequencies. Temporal compounding can be achieved by averaging sequential images with different weights assigned to each image. Another major technique for speckle removal is applying image filters. A good filter should smooth speckle effectively without damaging important information of the image. Linear speckle filters have been proven insufficient in suppressing speckle because they introduce blurring and mask diagnostically significant information [123], [124]. Nonlinear and adaptive filters have been developed by many researchers to smooth speckle. There are some filters developed on the signal dependent noise model to suppress speckle in synthetic aperture imaging (SAI) [56]-[59]. Some researchers discovered the speckle statistical models in different conditions [6]-[9], based on which many adaptive filters estimate the local speckle formations [51]-[55], [61]-[68]. They perform speckle reduction and feature preservation according to the estimation results. There are also many filters attempting to reduce speckle in wavelet domain [99]-[102], [109]. Recently, advanced image processing algorithms have been applied to suppress speckle, e.g. nonlinear diffusion [93]-[95] and

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neural networks [110], [111]. Although many methods have been developed for reducing speckle, few of them managed to achieve inspiring results. Speckle reduction remains its challenge in ultrasound imaging. This research is conducted to develop promising methods which can be used to suppress speckle in medical ultrasound images without damaging important image features.

1.3 Major Contributions of the Thesis

During the completion of the thesis, a spatial compounding and two image filters were developed, which can be used for reducing speckle in diagnostic ultrasound separately.

By applying both transmit and receive subapertures, the subarray compounding has been extended to the subaperture compounding, which can generate more number of images for averaging. Image correlations are analyzed in the developed subaperture compounding, in which subapertures are divided with different overlapping levels. In most spatial compounding methods, additional computations are required to find the overlapping area for compounding. The scan line steered technique is then developed and applied in the subaperture compounding to save such computation costs. The superiority of the subaperture compounding is verified using several sets of phantom data in radio frequency, compared to the subarray compounding.

Two multi-resolution filtering methods are developed to smooth speckle in medical ultrasound images. Both of them concentrate on filtering the Laplacian pyramid of the input image. One of the developed filters combines a noise smoother and an edge enhancer. The combination scheme is discussed in the thesis. And the other filter

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performs adaptive speckle filtering in each resolution of the input image. The adaptive filter is derived using the local speckle statistics. Both filters are tested using the real phantom and *in vivo* data to verify the effects on suppressing speckle.

1.4 Outline of the thesis

The research work concerned in this thesis concentrates on developing new methods for improving medical ultrasound image qualities. A spatial compounding method and two image filtering methods developed by us will be discussed.

In Chapter 2, methods developed for smoothing speckle are briefly reviewed. Speckle statistical model is introduced first to help understanding its formations. The compounding methods in spatial, frequency and temporal domains will be discussed then. Several typical filters for speckle reduction are covered in the remaining part of Chapter 2.

The newly developed spatial compounding is introduced in Chapter 3, which is called as the scan line steered transmit-receive subaperture compounding (SLSTRSC). The method employs different transmit-receive subaperture combinations in a phase array to generate the uncorrelated or partially correlated images. The non-overlap and overlap subaperture divisions are discussed with correlation analysis. The idea of scan line steering, which saves the computation cost to find the overlapping area for averaging in the common spatial compounding methods, is also described in the chapter. Real ultrasound data collected by the University of Michigan was used to test the method and the experiment results can be found in this chapter.

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The first image filtering method proposed for smoothing speckle is presented in Chapter 4. It performs noise reduction and edge enhancement at each pyramid representation of the input image simultaneously. The Laplacian pyramids (LP) of the input speckle image are first generated. Each LP layer is then processed by a selected filter. Besides a noise smoother, the filter also has a component of edge sharpener. Three such filters are discussed in the chapter. By selecting appropriate parameters for the smoothing and sharpening components at each LP layer, the discussed filters reduce noise efficiently without damaging fine structures of the layer. Therefore, efficient speckle suppression can be found in the reconstructed image from the processed LP layers, without losing important features of the original image. Simulations for evaluating the method were done using the synthetic ultrasound data, the real ultrasound data of a phantom, and *in vivo* data of a human liver. Both visual and quantitative comparisons showed that the new filters have good ability on smoothing speckle and preserving details.

Chapter 5 contains descriptions of the proposed adaptive pyramid filtering scheme for removing speckle in log-compressed ultrasound images. After getting the LP of the input noisy image, the Dutt filter for log-compressed ultrasound image is employed to smooth each LP layer based on local statistics. The virtual variance related to a LP layer, which indicates the speckle formation extent of the layer, is computed from the estimated variance of the layer and the operations involved in generating the layer. It is then applied as the controlling parameter of the Dutt filter, balancing the filter's performance between the maximum noise reduction and the best feature preservation. Experiment results using different ultrasound data sets showed that the proposed filtering scheme suppressed speckle in log-compressed images effectively without damaging important image details.

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The final chapter gives conclusions and discussions on the presented work. Some suggestions on the future work are presented based on this research results which can be undertaken based on this research.

Chapter 2

Review of Speckle Reduction Methods

Since the advent of B-mode ultrasonic imaging, ultrasound has been used at an ever increasing rate and established as one of the most important techniques in the field of medical diagnostic technology. The noninvasive nature, low cost, portability and real-time image formation constitute superiority of ultrasound imaging. However, ultrasound imaging suffers from a type of noise called as speckle [1]-[5], which degrades image qualities. Speckle tends to mask image details and increase the difficulties in diagnostic examinations. Hence, speckle reduction has been one of the areas on which researchers have been working to advance the ultrasound imaging.

2.1 Speckle formation and statistics

2.1.1 Speckle formation

Speckle in ultrasound imaging is caused by the interference of echo energy from randomly distributed scatterers within the resolution cell, which are too small to be resolved by the imaging system [1]-[5], [9], [10]. It can be modeled using a two-dimensional (2-D) random walk process [1], [5] (Fig. 2-1). When an ultrasound beam is

Chapter 2 Review of Speckle Reduction Methods

projected into human tissue, the echo from a resolution cell is the sum of the reflected signals from the scatterers within the cell. Due to the random locations and random reflectance of the scatterers, the backscattered signals from them have random phase and amplitude variations. Thus the complex summations in the different resolution cells have random results, i.e. the echo has a random amplitude. As ultrasound images are constructed using the amplitudes of the backscattered echoes, the random property leads to the occurrence of speckle.

Fig. 2- 1 Complex summation of backscattered signals represented by the 2-D random walk

Speckle is in a granular pattern and does not correspond to the actual tissue microstructure. It tends to mask the fine details, sometimes even causes wrong observation results. Fig. 2-2 illustrates the negative impacts caused by speckle. In speckle image (Fig. 2-2(b)), the edges of the circle are heavy blurred. And the uniform areas in the original structure show variable brightness due to speckle existence.

Fig. 2- 2 Illustration of speckle impacts on images

2.1.2 Speckle statistics

Speckle statistics is related to the statistical properties of the echo amplitudes, which have been derived by some researchers based on the different scatterer densities in a resolution cell [2] – [8].

If there is only one scatterer in the resolution cell, the echo reflected by it is approximately a spiculate wave. When there are two scatterers, the wave from each scatterer sums together at the phase sensitive transducer. These two waves can be in phase (maximum amplitude of the summed force), exactly out of phase (zero amplitude of the summed force), or any phase relationship in between, resulting in a summed force whose amplitude is between zero and the maximum. Adding more scatterers to the resolution cell increases the randomness of the echo signal phases from each scatterer. When the scatterer density is “large” (25 or more scatterers per resolution cell), the phases of the echoes become nearly uniformly distributed over 0 to 2π . This leads to the circular Gaussian statistics in the amplitude and phase of the summed echo. The echo magnitude can then be described using the Rayleigh distribution [2], [5]:

Chapter 2 Review of Speckle Reduction Methods

$$p(A) = \frac{A}{\sigma^2} e^{-\frac{A^2}{2\sigma^2}} \quad (2.1)$$

Where A is the amplitude of echo signals. σ^2 is the echo amplitude variance. In this condition, a so-called “fully developed” speckle is formed. A distinct property of the Rayleigh distribution is that the ratio of mean to standard deviation, which can be used to represent the speckle signal-to-noise ratio (SNR), has a fixed value of 1.91. This property has been used in many speckle smoothing filters as an indicator of fully developed speckle.

Deviations from the fully developed speckle occur when the number of the randomly positioned scatterers is not large. The K distribution is used to model the echo amplitude of this condition [6]-[8]:

$$p(A) = \frac{2c}{\Gamma(\alpha)} \left(\frac{cA}{2}\right)^\alpha K_{\alpha-1}(cA) \quad (2.2)$$

Where $K(.)$ is the modified Bessel function of the second kind, c is a scaling parameter. α represents the effective number of scatterers affecting echo envelope statistics.

When there are unresolved non-random located scatterers in the resolution cell, a spatial regularity exists in the echo signals, leading to an additional non-random coherent component in the echoes. The SNR of the echo envelope increases linearly with increase in the coherent component [5].

Chapter 2 Review of Speckle Reduction Methods

From above speckle statistics, we can see speckle carries information related to the statistical information of scatterers. It is helpful when we catalog tissue characters. However, as speckle always reduces the image contrast and the object detectability, it is expected to be smoothed in medical diagnostics. Many researchers have been working on methods of reducing speckle, which can be mainly classed into compounding and filtering [118], [119].

2.2 Compounding

Speckle is a kind of random noise but not in the same sense as, e.g. electrical noise [1], [9]. When an object is projected without changing any conditions, e.g. ultrasound pulse frequency, projecting angle, etc, speckle patterns in images obtained are identical. If the scan conditions change, speckle pattern changes, too. Hence, the basic principle of compounding for speckle reduction is to average several images of the same target which are acquired with different imaging conditions. The compounding results depend on the number of images applied in averaging and the correlation degree among them. Increasing the number of compounding images or decreasing their correlations leads to more compounding improvement. It has been proved that the maximum improvement can be reached through compounding is $\sqrt{N}$ (N is the number of images) on condition that all images for averaging are independent [1], [16], [17]. Compounding is often performed on three domains: spatial, frequency, and temporal.

2.2.1 Spatial Compounding

In spatial compounding, images containing different speckle patterns are obtained by varying the spatial orientation (i.e. illumination angle) of the transducer relative to the target. Initially, researchers moved the transducer linearly or circularly to get images with varied spatial orientation [1], [17], [20], [32]. Such procedure is depicted in the Fig. 2-3. Compounding of such methods can be performed only in the overlapping area (gray area in Fig. 2-3). Thus the images obtained have to be registered with accurate spatial information. A small error in recording spatial information or calculating the overlapping area will cause severe blur in the compounded image. The correlation degrees among obtained images depend on the ratio of the step size to the transducer size. Researches [1], [17] have proved that when the transducer is moved in a size equal to or great than the half length of the transducer, the obtained images can be considered as independent and hence, the maximum improvement of the compounding can be achieved. Later, Shattuck, etc, developed subarray compounding by applying a phased array [18]. The subarray is part of the array which is used as an independent transducer. Different subarrays were activated sequentially to generate images for compounding. In these methods, the

Fig. 2- 3 Spatial compounding by moving transducer (a) linearly (b) circularly

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correlation between the two images depends on the overlapping ratio of the corresponding subarrays [17]. If the subarrays are not overlapping, the images generated are uncorrelated and the compounding will reach the best result. Otherwise, images are partially correlated and the compounding gives less improvement.

A new method of spatial compounding imaging was discussed by Vera Behar, etc in their report [22]. In their method, the compounding system was constructed by three laterally placed transducers for image generations. The center transducer is a phased array, acting as a transmitter and receiver at the same time. The two side transducers contain only one element each and acted as unfocused receivers. Fig. 2-4 illustrates the imaging system. The individual images acquired by each receiver are used for compounding to reduce speckle. The improvement of the compounded image depends on the lateral distance a (shown in Fig.2-4) between the receivers.

Fig. 2- 4 Spatial compounding developed by Vera Behar.

An effective spatial compounding method is developed recently in some digital scanners. It is called as multi-angle compounding imaging (MACI). In MACI technique, each image for compounding has a predefined angle relative to the surface of the transducer by using the electronic steering [19], [21], [29]. These single-angle steered images are then

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superimposed to form the compounding result. The output image shape is determined by the superposition, with fully compounded area, partially compounded areas, and zero compounded areas. The MACI method is illustrated in Fig. 2-5. The compounding result of the MACI is decided by the number of images used and the angle difference between the two individual images.

Most spatial compounding methods are performed in the overlapping area only (gray area in Fig. 2-3), except the MACI. This requires images be registered with accurate spatial information. A small error may cause heavy blur in the compounded image. And additional computation costs are needed to find the overlapping area.

Fig. 2- 5 Illustration of MACI using 3 different angles.

2.2.2 Frequency compounding

Frequency compounding in ultrasound imaging processes the beamformed signal over

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two or more separate frequency bands to form images for superimposing [35]-[41]. Such images contain different speckle patterns due to the frequency-dependent reflection process within a resolution cell [35]. Fig. 2-6 shows a simple frequency compounding. The improvement of the frequency compounding is determined by the spectrum of band-pass filters applied. If the filters have no overlapped frequency spectrum, the obtained images are independent and the compounding reaches the best result. When the band-pass filters are overlapping, the signals after filtering will be partially correlated, and the compounding will have less improvement. Resolution loss is a problem of the frequency compounding because the resolution of the imaging is proportional to the reciprocal of the filter band width [35].

Fig. 2- 6 Illustration of frequency compounding using narrow band filters (NBF)

2.2.3 Temporal compounding

The temporal compounding is to combine a time series images for enhancing ultrasound image qualities [35], [42]. The time separation between adjacent images should be large enough to ensure the uncorrelated speckle patterns are contained. The temporal compounding can be expressed by the following equation:

$$\begin{aligned}
Y &= W \times X^T \\
X &= \{X_1, X_2, \dots, X_N\} \\
W &= \{w_1, w_2, \dots, w_N\}
\end{aligned} \tag{2.3}$$

where, Y is the output image, X is a vector of images in time series, W is the associated weight (or persistence) vector. W can be fixed, or varied to reduce the error caused by tissue moving [42], [53], [118]

Two problems are faced by all compounding methods due to the usage of multi images. One is the reduced frame rate [118], [119]. If we can not perform compounding until all images are ready, the frame rate will be greatly reduced and may not be accepted in real time imaging. Another problem is the moving blur caused by tissue motion [23], [53]. Because the compounding images are scanned at different time, a moving tissue structures with high speed will be at different positions in each image. Motion blur will occur when compounding such images. The degree of the motion blur depends on the number of compounding images and the speed of the moving structures. Severe errors are often observed when large number of images is used or the structure moves in a very high speed. Methods have been studied to alleviate the two problems [34], [53].

2.3 Image Filtering for Speckle Suppression

Image filtering is another technique often used for enhancing medical ultrasound images. It smoothes speckle in the current image before display using a signal filter. A good speckle filter is required to reduce speckle without damaging important features of the image. Generally, it should perform strong filtering in statistically homogeneous areas

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where fully developed speckle is often developed, while preserving features such as edges and point targets. In textured areas, it should achieve a compromise between noise reduction and feature preservations [51], [93], [119]. Compared with the compounding methods, it does not require special scanning settings to obtain multi images with different speckle patterns. However, implementing an image filter in hardware is difficult (Quantification errors in realizing the filter's coefficients always change the filter's behavior). Also an image filter always requires a large amount of calculations which may cost too much time to meet the real-time requirements. According to its formation and statistical properties, speckle is often regarded as a kind of multiplicative noise, which can not be smoothed by a simple linear filter. Various non-linear or spatially adaptive filters have been developed for speckle removal in different applications.

2.3.1 Speckle Reduction with Median Filters

The median filter is widely used in image enhancement because of its good performance at edge preserving and simplicity of implementation. It is often applied to images with impulsive noise [52]. The median filter is also used in ultrasound imaging to suppress speckle. However, it does not give satisfying results because the specific property of speckle [117].

To overcome direct median filter's defect, Loupas et al. [52] developed an adaptive weighted median filter (AWMF). The filter output is a weighted median, which is defined as the pure median of an extended sequence from the original sequence constructed by the pixels in the filter window. The extended sequence is formed by repeating each pixel in the original sequence a number of times indicated by its associated weight. And the

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weight linked to a specific pixel is computed adaptively, using the local statistics and the distance of the pixel to the center pixel of the filter window, as the following:

$$w(i, j) = \text{round} [w(K + 1, K + 1) - cd\sigma^2 / \mu] \quad (2.4)$$

where $w(i, j)$ is the weight for pixel $x(i, j)$ in a filter window whose size is $2K + 1$ by $2K + 1$. $w(K + 1, K + 1)$ is the weight for the center point. c is a scaling constant. μ and σ^2 are the local mean and variance inside the filter window, separately. And d is the distance of the pixel $x(i, j)$ to the center pixel of the filter window. The operation of $\text{round}(x)$ denotes to calculate the nearest integer to the value x if it is above zero. The AWMF method can then be expressed as:

$$y_{AWMF} = \text{median} \{ \text{EXTD}(X, W) \} \quad (2.5)$$

where, X is the sequence containing pixels inside the filter window, and W is the weight vector containing all weights computed for items of X . $\text{EXTD}(X, W)$ represents the extension of the sequence X with associated weights W .

The local statistically based calculations provide the AWMF a space-varying property when filtering. And the selection of the weight coefficients represents a trade-off between noise reduction and signal preservation [52]. In uniform areas in which speckle is fully developed, values of σ^2 / m will be small. And c has been chosen so that the value of $cd\sigma^2 / m$ is low, causing maximum speckle reduction performed. However, when the pixel is in the region containing a resolvable structure or a boundary, the large value of σ^2 / m will give additional weight to centrally located pixels. Consequently, little smoothing will be performed and fine image detail can be preserved.

On the basis of AWMF, Richard et al. [65] proposed the directional adaptive weighted median filter to further enhance line segments in images. There are also mode filters of the similar structure developed for speckle reduction [117].

2.3.2 Adaptive Unsharp Speckle Filters

The unsharp filter enhances edges and other high frequency components in an image via a procedure which subtracts an unsharp, or smoothed, version of an image from the original image. It is commonly used for sharpening edges in noisy images [130], [131]. There are many speckle filters utilizing a space-varying unsharp operator [51], [54]-[57], [61]-[63], [66], [67]. They permit a varying degree of speckle reduction at different areas in the image according to the local speckle pattern from the fully developed speckle. In general, with the help of the unsharp masking operator, such filters achieve a balance between direct averaging in homogeneous regions and the all-pass filter (preserve the original pixel value) when regions contain fine structures, such as edges and point targets.

The two-dimensional (2-D) unsharp masking filter has a structure as the following:

$$\hat{R}(x, y) = \bar{I}(x, y) + k(x, y) \cdot (I(x, y) - \bar{I}(x, y)) \quad (2.6)$$

where, $\hat{R}(x, y)$ is the output pixel value of the filtered image whose grid coordinates is (x, y) . $I(x, y)$ is the pixel value of the input speckle image. $\bar{I}(x, y)$ is the local mean of the filter window in the input image with the center of (x, y) . $k(x, y)$ is a scaling parameter ranging from zero to one. It controls the filter's output between the direct averaging and the original value, i.e. the maximum and least filtering. In an unsharp

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speckle filter, scaling parameter $k(x, y)$ is computed as the measurement of the similarity of the local speckle pattern to the fully developed speckle.

Lee [58] and Kuan [61] first developed their filters with an unsharp structure to suppress speckle in synthetic aperture radar (SAR) imaging. Lee [56] adapted the additive noise filter to the multiplicative speckle model by introducing a linear approximation which transferred the multiplication of the signal and the uncorrelated noise to the sum them. In the Lee filter, the scaling parameter $k(x, y)$ of the unsharp operator is computed as:

$$k(x, y) = 1 - \frac{C_N^2}{C_I^2(x, y)} \quad (2.7)$$

where, C_N^2 is the noise variation constant representing the fully developed speckle in the input image. It can be calculated as the ratio of the variance to the mean over a fully developed speckle area. And $C_I^2(x, y)$ is the ratio of the local standard deviation to the local mean as the following:

$$C_I^2(x, y) = \sigma_I(x, y) / \bar{I}(x, y) \quad (2.8)$$

. where, $\sigma_I(x, y)$ is the local pixel standard deviation in the filter window.

Kuan [58] used the linear minimum mean square error (MMSE) estimation on the multiplicative speckle model. He derived the scaling factor $k(x, y)$ with a similar result as Lee:

$$k(x, y) = [1 - \frac{C_N^2}{C_I^2(x, y)}] / [1 + C_N^2] \quad (2.9)$$

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The Lee and Kuan filters have the defect that they need to verify the area containing the fully developed speckle manually. Although Bamber *et al* used the same local statistical parameter to compute the scaling factor $k(x, y)$ [51], [61], one filter developed by them solve the defect [61] and the scaling factor $k(x, y)$ was computed using the following equation:

$$k(x, y) = (C_I^2(x, y) - C_{I \min}^2) / (C_{I \max}^2 - C_{I \min}^2) \quad (2.10)$$

where, $C_{I \min}^2$, $C_{I \max}^2$ are the minimum and the maximum values of $C_I^2(x, y)$ in the input speckle image, respectively.

Some researchers used the speckle statistical model, the Rayleigh and K distributions, to examine the local speckle pattern and calculate the scaling factor $k(x, y)$ for the unsharp operator. Evans, *et al*, developed their speckle filter based on a property of speckle statistics: for fully developed speckle, the SNR has an expected value of 1.91. The scaling factor $k(x, y)$ in their filter can be computed as [53]:

$$k(x, y) = r \cdot (SNR(x, y) - 1.91) \quad (2.11)$$

where, $SNR(x, y)$ is the local SNR, r is a constant controls $k(x, y)$ lie between zero and unity.

Through analyzing different orders of statistical moment using the Rayleigh and K distributions, Dutt derived a similarity parameter from the local speckle pattern to the fully developed speckle. The similarity parameter is then used to calculate the scaling factor $k(x, y)$ for implementing the Dutt adaptive unsharp speckle filter [55]:

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$$k(x, y) = 1 - \frac{2}{\sqrt{\pi}} \cdot \frac{\bar{I}(x, y)}{\sqrt{I(x, y)^2}} \quad (2.12)$$

where, $\bar{I}(x, y)^2$ is the local square average.

In an adaptive unsharp speckle filter, when pixels under processing are in the image region consisting of fully developed speckle (commonly a homogeneous area), the scaling factor $k(x, y)$ will have a value closing to zero. Thus the filter will output the local average for the maximum smoothing. When pixels are in the region containing edges or resolvable structures, $k(x, y)$ will be close to unity. In this case, the filter output is approximate to the original value for saving structures. In other areas, the filter achieves a compromise between the noise removal and features preservation.

The efficiency of the adaptive unsharp speckle filters depends on the accuracy of the speckle model applied and the local statistics estimations. An advantage of such filters is that they are easy to implement because of the simple structures.

2.3.3 Speckle Reduction Using Diffusion Methods

Diffusion methods have recently been studied by many researchers in the image processing field. The advantages of applying diffusion include robust noise smoothing and enhancing edges [93]. The basic anisotropic diffusion was developed by Perona and Malik (PMAD) [92]. They gave the fundamental partial differential equations (PDE) based diffusion equation for image smoothing in a continuous form:

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$$\begin{aligned}\frac{\partial I(x, y, t)}{\partial t} &= \text{div}[c(x, y; t) \cdot \nabla I(x, y, t)] \\ I(x, y, t = 0) &= I_0(x, y)\end{aligned}\quad (2.13)$$

where, $I(x, y, t)$ is the image pixel value at time t , whose grid coordinates is (x, y) .

$\frac{\partial I(x, y, t)}{\partial t}$ is the rate of value changing of the processing pixel at time t . $\text{div}[\cdot]$ is the divergence operator. $c(x, y; t)$ is the diffusion coefficient at time t associated to the processing pixel at (x, y) . $\nabla I(x, y, t)$ represents the gradient of the image at the processing pixel and $I_0(x, y)$ is the initial value of the processing pixel. The divergence operator can be spread as the following:

$$\frac{\partial I(x, y)}{\partial t} = c(x, y; t) \cdot \nabla^2 I(x, y, t) + \nabla[c(x, y; t)] \cdot \nabla I(x, y, t) \quad (2.14)$$

and $\nabla^2 I$ can be calculated using the Laplacian operator:

$$\nabla^2 I = I(x+1, y) + I(x-1, y) + I(x, y+1) + I(x, y-1) - 4I(x, y) \quad (2.15)$$

Two diffusion coefficient suggested by Perona and Malik [91]:

$$\begin{aligned}c(\nabla I) &= \exp[-(\nabla I / k)^2] \text{ or} \\ c(\nabla I) &= \frac{1}{[1 + (\nabla I / k)^2]}\end{aligned}\quad (2.16)$$

where, k is a constant of edge magnitude.

Many diffusion methods have been developed based on the PMAD structure for noise smoothing and edge enhancement. The diffusion coefficient is the key factor in noise smoothing process. Most diffusion methods work well for images with additive noise [93].

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However, they can not be used to smooth speckle in medical ultrasound images as speckle is a kind of signal-dependent, spatially correlated multiplicative noise. To apply diffusion in speckle corrupted images, Yu and Acton [93] developed their method of speckle reducing anisotropic diffusion (SRAD) by replacing the diffusion coefficient of the PMAD algorithm with a speckle scaled one. The new speckle scaled diffusion coefficient $c(x, y; t)$ is defined as the following:

$$\begin{aligned} c(q) &= 1 / \{1 + [q^2(x, y; t) - q_0^2(t)] / [q_0^2(t)(1 + q_0^2(t))]\} \text{ or} \\ c(q) &= \exp\{-[q^2(x, y; t) - q_0^2(t)] / [q_0^2(t)(1 + q_0^2(t))]\} \end{aligned} \quad (2.17)$$

where, $q_0(t)$ is the speckle scale function controlling the smoothing process. It can be estimated by:

$$q_0(t) = \frac{\sqrt{\text{var}[z(t)]}}{\overline{z(t)}} \quad (2.18)$$

$\text{var}[z(t)]$ and $\overline{z(t)}$ are the intensity variance and mean over a homogeneous area z (which contains the fully developed speckle) at time t , separately.

And $q(x, y; t)$ can be calculated by:

$$q(x, y; t) = \sqrt{\frac{\frac{1}{2} \cdot \left(\frac{|\nabla I(x, y; t)|}{I(x, y; t)}\right)^2 - \frac{1}{4^2} \cdot \left(\frac{\nabla^2 I(x, y; t)}{I(x, y; t)}\right)^2}{\left(1 + \frac{1}{4} \cdot \frac{\nabla^2 I(x, y; t)}{I(x, y; t)}\right)^2}} \quad (2.19)$$

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In the SRAD method, the variation coefficient $q(x, y; t)$ served as an edge detector. It has large values at edges or high-contrast features and small values in homogeneous regions. The modification of the diffusion coefficient will encourage more isotropic diffusion in homogeneous regions, whose accumulative effect will increase the ability of speckle removal. In the areas containing edges, ‘negative’ diffusions will occur along the edge direction on the both sides of an edge. This is different from the conventional anisotropic diffusion, where the diffusion in the edge direction will be gradually suppressed as the center of the edge is becoming near. The accumulative effect of this ever-existing ‘negative’ diffusion has the result of sharpening edges: the dark side of the edge goes to darker and the bright side of the edge goes to brighter.

Another approach for speckle reduction based on nonlinear coherent diffusion modal was proposed in [94]. The new model performs smoothing according speckle extent and image anisotropy. Several diffusion methods recently developed can be found in [95].

The diffusion methods have their own disadvantages. First, the convergence issue is a challenge. If the step size is small, the diffusion may cost quite a lot of time to reach the convergence. If the step size is large, it may result over diffusion and cause blur. Second, anisotropic diffusion filter has to face the difficulty of designing the constant force, which frequently depends on the users’ experience and is not desired.

2.3.4 Filtering in the wavelet domain

Wavelet analysis has the useful property of space and scale localization which provides great promise for signal processing at different scales [97], [98]. It has been successful

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applied in a variety of signal processing problems, including image denoising. Many algorithms based wavelet transform have been developed recently for removing speckle in SAR images and medical ultrasound images [99]-[103], [107], [108].

Speckle reduction in the wavelet domain consists of three steps: wavelet transforming, denoising, and data reconstruction, which is illustrated in Fig. 2-7. Image transforming to the wavelet domain and reconstruction are accomplished by using a series of 2-D discrete wavelet transform (DWT) and Inverse DWT (IDWT), respectively. Multiscale representations of the original image are then obtained, each of which belongs to a distinct subband. Denoising is then performed in each subband by manipulating the wavelet coefficients, which can be generally classified into two main approaches: thresholding and shrinkage [98], [101]. The technique of thresholding involves a binary decision of “keeping” or “killing”. A simple way to implement the binary decision is introduced in [98]: it will be set to zero (“killing”) if the value of wavelet coefficient is less than the threshold selected; otherwise keep its original value. The denoising effect of the thresholding relies on the selection of the threshold. Too small threshold will lead to insufficient noise removal while too large threshold will damage important image details. Besides a universal constant threshold [98], spatially adaptive thresholds and multiple thresholds were proposed by researchers to improve the thresholding performance [99], [100], [101], [102]. The shrinkage technique involves assuming a priori distribution associated with the wavelet coefficients of noise free image in each scale, and estimating the wavelet coefficients using the maximum a posteriori (MAP) estimator or the minimum mean- square error (MMSE) estimator. The enhancing result of the shrinkage technique is determined by the choice of prior distribution made for the wavelet

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coefficient. Different prior distributions have been reported by some researchers for smoothing speckle noise [101], [105], [106].

Fig. 2- 7 Illustration of speckle reduction in wavelet domain

2.4 Summarizations

Speckle in coherent imaging is caused by summing random distributed complex backscattered signals from scatterers which can not be resolved by the imaging system. Unlike other random noise, for example, electronic noise, speckle pattern does not change if the imaging conditions keep unchanged. This property leads to the generations of the compounding techniques for speckle reduction, which average images with varied speckle patterns obtained in different imaging conditions. The method of obtaining compounding images by changing the positions of the imaging array relative to the target is referred as the spatial compounding. Frequency compounding is carried out by forming the images in different frequency. Temporal compounding uses a sequence of images among which varied speckle patterns have been developed due to the enough time gaps between adjacent images. Compounding techniques have the shortcomings of reducing the frame rate and causing the moving blur due to the requirement of using multi images. When ultrasound wave travels in the tissues, spatial variations in sound speed result in differences in image registration, which leads to blurring in spatial compounding. Spatial compounding also often requires distinct transducer arrays or imaging procedures. Image filtering is another type of technique often used to remove speckle. A good filter for

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speckle reduction is required to smooth speckle efficiently without losing important image features. Besides filters introduced above, there are also filters for speckle suppression using neural networks [110], [111], adaptive window shape and size [114], [115], etc. Although there are many filters developed for reducing speckle in medical ultrasound images, few of them achieve inspiring results because the complex structure of human tissue. Furthermore, speckle filters share some common disadvantages which limit their capabilities. Firstly, ultrasound imaging system contains a logarithm compression to meet the dynamic range of the display system. Most filters are designed on the basis of signal dependent multiplicative speckle model, which is derived using the echo signals without logarithm compression. Hence, these filters need to redesign to fit for the logarithm compressed model or process image data before logarithm compression. However, acquiring image data before logarithm compression is not easy. Secondly, most filters contains large computations which make them time consuming. The requirements for real-time applications may not be met and the filters have to be used in an off-line mode.

Chapter 3

Proposed Scan Line Steered Transmit-Receive Subaperture Compounding Using a Phased Array

3.1 Introduction

Image qualities in medical ultrasound are often degraded by an inherent noise known as speckle [1], [2]. The presence of speckle masks fine details and reduces the diagnostic accuracy. A goal of enhancing medical ultrasound images addresses speckle removal. Speckle suppression can be accomplished by compounding and filtering. Compounding averages multiple images of the same target obtained under different imaging conditions. It enhances the stationary signal, i.e. tissue structures, while reducing the varying speckle noise. Compounding can be implemented in spatial, frequency, and temporal domains, separately [109], [124].

In spatial compounding, the images for averaging are commonly obtained by varying the ultrasound spatial orientations (i.e. illumination or receiving angle) of the aperture relative to the target [1], [17]-[32]. A kind of spatial compounding can be achieved by obtaining multiple images through subarrays [17], [18], [25], which can be referred as the subarray compounding. A subarray contains partial array elements and is used as an independent transducer during an image construction period. In compounding, degree of improvement

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in the composite image depends on the number of averaging images and correlations among them [1], [17]. Increasing the number of images can acquire better compounding results. In subarray compounding, the largest number of images for averaging equals to the number of subarrays divided. To obtain better results in subarray compounding, we need to increase the number of images for averaging. This can be achieved by using a larger transducer at the cost of increasing the cost.

In this study, a spatial compounding method referred as transmit-receive subaperture compounding (TRSAC) was developed. The method can generate more number of images for compounding than the subarray compounding does when the two methods use the same phased array. In TRSAC, the phased array is divided into several subapertures of equal length, each of which can be used as a transmitter or receiver independently. An image for compounding is acquired by activating a transmit subaperture (TSA) and a receive subaperture (RSA) during an image construction turn. Each combination of a TSA and a RSA represents a specific ultrasound orientation. Compared to the subarray compounding in which the same subaperture is used for ultrasound transmitting and receiving, the distinction of the proposed method is that the ultrasound transmitter and receiver can be the same subaperture or not. By these subaperture combinations, the number of the averaging images is increased and better compounding results can be achieved. In TRSAC, two types of subapertures were studied: non-overlapping and overlapping.

The scan line steered (SLS) technique is used in the TRSAC method to avoid finding the overlapping areas for compounding. Utilizing the electronic steering technique, echo signals collected by different RSAs are steered to form a predefined set of scan lines in

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the scanning area. Hence, images constructed from different TSA and RSA combinations consists of same scan lines and can be used in averaging directly. The SLS technique can also be used in those spatial compounding methods using phased arrays, e.g. the method reported by Shattuck [18].

In the following sections, the proposed spatial compounding is analyzed in details. The theoretic models of the subarray compounding and the proposed TRSAC method are given using the scan line representations. Non-overlapping and overlapping subaperture partitions are discussed in the proposed method. The correlation between the two adjacent subaperture combinations are then analyzed, which decides the compounding improvement degree. The SLS technique is illustrated and then applied in simulations, which are carried out to verify the performance of the new method using the phantom data sets collected by the University of Michigan.

3.2 Analysis of the Proposed TRSAC

3.2.1 Theoretic Model

An ultrasound image is formed by obtaining a number of scan lines inside the scanning area. The formulation of a scan line in a conventional B-mode imaging system can be expressed as [14]:

$$A_l(t) = \sum_{i=1}^K \sum_{j=1}^K \sum_{p=1}^M \rho_p S\left(t - \frac{R_{ip}}{c} - \tau_{il} - \frac{R_{jp}}{c} - \tau_{jl}\right) \quad (3.1)$$

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where $A_l(t)$ is the echo amplitude function of the l^{th} scan line. K is the transducer element number and M is the scatterer number in the observing area. i and j correspond to the transmit and receive elements in the transducer, respectively. R_{ip} and R_{jp} are the distances from the i^{th} transmitting element and j^{th} receive elements to the p^{th} scatterer, separately. c represents the sound wave speed. τ_{il} and τ_{jl} are the time delays for beamforming at scan line l associated to elements i and j . ρ_p denotes the reflectivity of p^{th} scatterer and $S(t)$ is the ultrasound pulse function.

An image can then be constructed by obtaining the assembly of amplitudes of all scan lines required:

$$I(t) = \{ amp(A_1(t)), amp(A_2(t)), ..., amp(A_L(t)) \} \quad (3.2)$$

where $I(t)$ represents the image constructed at time t . L is the number of scan lines required. $amp(.)$ denotes computing the amplitude.

Utilizing the equations (3.1) and (3.2), we can derive the models for the subarray compounding and the proposed TRSAC.

3.2.1.1 Model for the Subarray Compounding Model

Subarray compounding is first developed by Shattuck, *etc* [18]. The subarray is a part of the array which is used as an independent transducer. Based on equation (3.1), a scan line

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constructed from a subarray can be expressed by dividing the transducer elements into subarray groups as the following:

$$A_{r,l}(t) = \sum_{i \in SA_r} \sum_{j \in SA_r} \sum_{p=1}^M \rho_p S\left(t - \frac{R_{ip}}{c} - \tau_{il} - \frac{R_{jp}}{c} - \tau_{jl}\right) \quad (3.3)$$

where $r = 1, 2, \dots, N$ and N is the number of subarrays divided. $A_{r,l}(t)$ is the l^{th} scan line formed by the r^{th} subarray.

The image of this subarray can then be represented by:

$$I_r(t) = \{ \text{amp}(A_{r,1}(t)), \text{amp}(A_{r,2}(t)), \dots, \text{amp}(A_{r,L}(t)) \} \quad (3.4)$$

where $I_r(t)$ is the image obtained through the subarray r at time t .

The number of images used in subarray compounding is equal to the number of subarrays divided. The subarray compounding can be formulated using the following equation:

$$I_{comp}(t) = \frac{I_1(t) + I_2(t) + \dots + I_N(t)}{N} \quad (3.5)$$

3.2.1.2 Model for the Proposed TRSAC method

Like subarray compounding, subaperture processing is a multi-element synthetic aperture approach [34]. A subaperture also contains partial transducer. Differently, in our TRSAC method a subaperture is not required working for ultrasound transmission and echo receiving simultaneously. A virtual transducer is formed by combining an active TSA and

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RSA during an image construction cycle. The TSA and RSA of the virtual transducer, of course, can be the same or not. By applying the transmit-receive subaperture combinations, the number of images for compounding will be increased. Generally, if N subapertures are divided, there will be N^2 virtual transducers formed at most, each of which can be used to generate a compounding images. The increased images will benefit the compounding effect. Fig. 3-1 presents an example of subaperture combinations using 3 subapertures. They are numbered from 1 to 3 in the transducer. A virtual transducer, for example, is formed by combining the first TSA and the second RSA, which is represented as $TSA_1 - RSA_2$. Totally, there will be 9 (3^2) different virtual transducers in Fig. 3-1.

Fig. 3- 1 Illustration of forming virtual transducers by combining TSAs and RSAs

The formulation of a scan line constructed from a virtual transducer can be expressed by grouping the transducer elements into subapertures as the following:

$$A_{r-q,l}(t) = \sum_{i \in TSA_r} \sum_{j \in RSA_q} \sum_{p=1}^M \rho_p S\left(t - \frac{R_{ip}}{c} - \tau_{il} - \frac{R_{jp}}{c} - \tau_{jl}\right) \quad (3.6)$$

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where $r, q = 1, 2, \dots, N$ and N is the number of subapertures divided. $A_{r-q,l}(t)$ is the l^{th} scan line formed through the virtual transducer $TSA_r - RSA_q$.

The image of this virtual transducer is then formed as:

$$I_{r-q}(t) = \{ \text{amp}(A_{r-q,1}(t)), \text{amp}(A_{r-q,2}(t)), \dots, \text{amp}(A_{r-q,L}(t)) \} \quad (3.7)$$

Through the equation (3.7), we can find that the proposed subaperture compounding generates N^2 images for averaging, which is larger than the number of images generated in subarray compounding. And the proposed subaperture compounding can be expressed as the following:

$$I_{comp}(t) = \frac{\sum_{r=1}^N \sum_{q=1}^N I_{r-q}(t)}{N^2} \quad (3.8)$$

3.2.2 Non-overlapping and Overlapping Subapertures

Spatial resolution needs to be considered when doing the compounding. Spatial resolutions in ultrasound imaging, including the axial resolution and the lateral resolution, are factors influencing the ultrasound image qualities. The axial resolution describes the scanner's ability to detect the smallest resolvable objects along the beam's propagating direction. It depends mostly on the length of the spatial ultrasound pulse, which is determined by the transducer center frequency and its damping factor. Therefore, the axial resolution will not be affected much if partial elements of the transducer are used. The lateral resolution describes the system's ability to distinguish structures that are closely positioned within the image plane along a line perpendicular to the beam's

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propagating direction. It mainly depends on the beam width, which is theoretically proportional to the reciprocal of the active aperture size under the ideal conditions. Hence, when we divide subapertures along a transducer, the size of them should be considered to meet the requirements of the lateral resolution. Non-overlapping and overlapping are the two types of the subapertures can be divided in a transducer. They require different transducer sizes to achieve the equal lateral resolutions.

Fig. 3- 2 (a) Non-overlapping and (b) overlapping subapertures

In non-overlapping subapertures (Fig. 3-2(a)) no element is contained simultaneously by different subapertures. The number of the non-overlapping subapertures can be divided in a transducer is limited by the lateral resolution requirement and the transducer size. For example, only two non-overlapping subapertures can be partitioned in a transducer if the lateral resolution demands half size of that transducer at least. To increase the number of non-overlapping subapertures, we can either employ a larger transducer or allowing a downgraded lateral resolution. Overlapping subapertures permit same elements being contained by several subapertures simultaneously (Fig. 3-2(b)). The number of the overlapping subapertures can be divided in a transducer is determined by the lateral resolution requirement, the transducer size, and the overlapping size together. Allowing overlapping makes it possible to divide several subapertures in a small transducer without downgrading the lateral resolution. Under the requirement of a specific lateral resolution,

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the size of the transducer on which a number of overlapping subapertures are divided will be smaller than that of the transducer with the same number of the overlapping subapertures partitioned. For example, supposing the lateral resolution requires a 32-element aperture size, to obtain two non-overlapping subapertures requires a 64-element array, while a 48-element array can be used if two overlapping subapertures are divided with 16-element overlaps.

3.2.3 Correlation Analysis of Subaperture Combinations

Results of a spatial compounding are influenced by the correlations between the two individual images for averaging. In the TRSAC such correlations are decided by the correlation degree between the two corresponding virtual transducers, i.e. the subaperture combinations. The discrete effective transmit-receive aperture function [22] can be employed to estimate the correlation between the two adjacent virtual transducers. Here the two adjacent virtual transducers means that the TSAs of them are same and the RSAs are adjacent, or vice versa. The discrete effective transmit-receive aperture function is the linear convolution of the discrete TSA and RSA functions [23], both of which are vectors of size K (K is the element number of the entire transducer). The components of a discrete TSA function are binary values determined by the following rules:

- If the i^{th} element is contained in the TSA, the i^{th} component in the TSA vector is set as one;
- Otherwise, zero.

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To calculate the effective transmit-receive aperture functions, the elements of the transducer are numbered from 1 to K and the subapertures divided in the transducer are numbered from 1 to N . If the p^{th} subaperture contains elements whose indexes are from m to n and it is used as a TSA, its discrete transmit function e_T will then be a vector of size K with $n - m + 1$ non-zero components, which can be written as the follow:

$$e_{T(p)} = [a_1, a_2, \dots, a_m, a_{m+1}, \dots, a_n, a_{n+1}, \dots, a_K] \quad (3.9)$$

where $a_i = 1$ if $i \in [m, n]$ and $a_i = 0$ if $i \notin [m, n]$.

The discrete function of a RSA can be obtained using the same rules. For example, when the p^{th} subaperture mentioned above is used as a RSA, the discrete receive function e_R will be the same as e_T :

$$e_{R(p)} = [a_1, a_2, \dots, a_m, a_{m+1}, \dots, a_n, a_{n+1}, \dots, a_K] \quad (3.10)$$

The two-way effective aperture function of a transmit-receive subaperture combination is the linear convolution of the discrete TSA and RSA functions:

$$e_{T(p)-R(q)}(s) = \sum_{i=1}^K e_{T(p)}(i) e_{R(q)}(n-i) \quad (3.11)$$

Where, $p, q = 1, 2, \dots, N$ and $s = 1, 2, \dots, 2K - 1$. The normalized effective aperture function $e_{T(p)-R(q)}^*(s)$ is then calculated as:

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$$e_{T(p)-R(q)}^*(s) = \frac{e_{T(p)-R(q)}(s)}{\sum_{s=1}^{2K-1} e_{T(p)-R(q)}(s)} \quad (3.12)$$

If the two virtual transducers are represented by $TSA_{p1} - RSA_{q1}$ and $TSA_{p2} - RSA_{q2}$, separately, then the correlation coefficient between them can be computed using their normalized effective aperture functions as the following:

$$r(p1, q1, p2, q2) = \sum_{s=1}^{2K-1} e_{T(p1)-R(q1)}^*(s) \cdot e_{T(p2)-R(q2)}^*(s) \quad (3.13)$$

where, $r(p1, q1, p2, q2)$ represents the correlation coefficients of the two subaperture combinations.

An example of using discrete effective transmit-receive aperture functions to calculate correlation coefficients among subaperture combinations is shown here. A transducer of 64 elements was used in the example. The correlations among subarrays were also computed for comparisons. Different numbers of the non-overlapping subapertures are first divided. Through the equations (3.4) ~ (3.8), the correlation coefficients between any two adjacent subarrays are calculated as zero. This is in accordance with previous research results shown in [1] and [17]. Correlation coefficients computed between the two adjacent virtual transducers are shown in the Fig. 3-3. The x-coordinate of the figure denotes the number of non-overlapping subapertures divided.

In practical ultrasound imaging, apodization is often applied in the receive aperture to reduce side lobe effects of the transducer. With receive apodization, the discrete RSA function of the equation (3.5) will be:

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$$e_{R(p)} = [b_1, b_2, \dots, b_m, b_{m+1}, \dots, b_n, b_{n+1}, \dots, b_K] \quad (3.14)$$

where b_i represents the coefficients applied for apodization if $i \in [m, n]$ and $b_i = 0$ if $i \notin [m, n]$. The correlation coefficients between the two adjacent subaperture combinations with the Hamming coefficients as the receive apodization are computed and also shown in Fig. 3-3.

Fig. 3- 3 Correlations between adjacent non-overlapping subaperture combinations.

In the Fig. 3-3, we can see the correlation coefficients between the two adjacent transmit-receive subaperture combinations (i.e. virtual transducers) without applying receive apodization are almost a constant value of 0.25. The same result can be derived using the methods reported previously in [2] and [17], by setting the translate distance between the virtual transducers as half of subaperture size. In this case, the two adjacent virtual transducers can be considered as lowly correlated and the echo signals obtained from

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them are ‘almost’ independent [2]. In the Fig. 3-3, we can find that applying receive apodization can reduce the correlations between the subaperture combinations.

Two overlapping subapertures were then divided in the same 64 element array. Each subaperture has 32 elements. The overlapping ratio, which is defined as the ratio of the overlapping size to the subaperture size, was increased from 0.06 to 0.77. The Hamming coefficients were applied to implement the receive apodization. The correlations were computed with and without applying the receive apodization, separately. The results are shown in the Fig.3-4. Besides correlation coefficients between the two adjacent subaperture combinations, the correlations between the subarrays are also computed for

Fig. 3- 4 Correlations between 2 overlapping subarrays and adjacent subaperture combinations using 2 overlapping subapertures.

comparisons. In the proposed subaperture compounding, two subapertures are activated to work as the transmitter and receiver, separately. They can be the same subaperture or not.

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However, in subarray compounding, one subaperture is activated for transmitting and receiving simultaneously like an independent array.

In the Fig. 3-4, we can see that smaller correlation coefficients were obtained when applying the receive apodization. Hence, applying the receive apodization will improve the performance of the TRSAC method and the subarray compounding because it decreases the correlations among the averaging images. We can also see that when the ratio of the overlapping size to the subaperture size increases, the correlation curves of the subarrays and subaperture combinations also rises. Compared with the values of the subarray, the correlation coefficients between the two adjacent subaperture combinations are much larger and reach the high correlation degree first. For example, when the overlapping ratio is 0.5, the correlation between the two adjacent subaperture combinations with receive apodization is about 0.6, while the correlation between the two subarrays is only about 0.15. When the two subapertures are high correlated, the compounding effects will be decreased greatly.

Comparing curves in Fig. 3-3 and Fig. 3-4, one can conclude that the correlation coefficient between two non-overlapping subapertures is less than that between two overlapping subapertures. Applying overlapping between subapertures saves the transducer size. However, allowing overlapping among subapertures increases the correlations of the echo envelope signals obtained by each subaperture. As a result, the correlations between individual images generated from different subaperture combinations are also increased. Therefore, the compounding improvement obtained by employing overlapping subapertures is less than that achieved by using the same number

of non-overlapping subapertures. Larger overlapping size applied, less improvement will be found in the compounded images.

3.2.4 Improvement Incorporating Lateral Resolution and Speckle

Reduction in the Proposed Method

The proposed subaperture compounding loses the lateral resolution to some extents as it employs parts of the transducer for ultrasound casting and receiving, when comparing with a scanning system using the entire transducer array. The axial resolution will not be affected as it is related to the center frequency of the transducer. Such lateral resolution loss deteriorates the object identification ability of the scanning system. On the other hand, the compounding improves the output image qualities by suppressing speckle. The two opposite factors exist in the proposed compounding simultaneously and the output image quality depends on the incorporated result of them.

In [16], Smith *et al.* proposed a model of an ideal observer for the task of identifying a lesion within a uniform background. It quantifies the expected trade-off between speckle reduction and the resolution loss. Referring to Smith's work, O'Donnell and Silverstein [17] developed an alternative measure for the compounding systems employing part of the transducer array. It also estimates the compromised image improvement combining speckle reduction and lateral resolution. The measure is defined as the following:

$$\eta = \frac{L_s}{L} N_{eff} \quad (3.15)$$

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where L_s is the length of the subaperture used, which is divided in an aperture of length L . L_s / L represents a measure of the lateral resolution of the imaging system. It equals to unity if the entire aperture is used in the system for ultrasound transmitting and receiving. If it is smaller than unity, the resolution loss exists. N_{eff} represents the equivalent number of independent images generated for the compounding. Researchers have already proved that the SNR improvement provided by the spatial compounding is proportional to $\sqrt{N_{eff}}$ [1], [17]. The larger the N_{eff} is, the more speckle will be suppressed in the compounded image. N_{eff} can be computed using the speckle contrast, which is defined as the following [17]:

$$N_{eff} = \left[\frac{1}{C(N)} \right]^2$$

$$C(N) = \frac{1}{\sqrt{N}} \left[1 + \frac{2}{N} \sum_{m=1}^{N-1} (N-m)r(m) \right]^{1/2} \quad (3.16)$$

where $C(N)$ is defined as the speckle contrast. N is the number of images generated for the compounding. m is the index difference between two images, ranging from 1 to $N-1$. $r(m)$ is the correlation coefficient between two images.

Integrating the lateral resolution and speckle reduction, η shows the incorporated result in the compounded image compared to the conventional imaging system employing the entire aperture. Consequently, any increase over unity of η represents that improvements have been obtained over the single measurement using the entire aperture.

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In this study, η is computed to show compounding improvement in the proposed method incorporating speckle reduction as well as the lateral resolution. In the following computations, two subapertures are divided in the entire aperture. The overlapping ratios between the overlapping subapertures are set from 0 to 0.75. Using the equation (3.16), the equivalent number of independent images, N_{eff} , in the proposed compounding is first computed. N_{eff} is also computed for the subarray compounding as a comparison, using subarrays whose sizes are the same as those of the subapertures.

For subarray compounding using the two subarrays, the equation (3.16) becomes to:

$$\begin{aligned} C(N) &= \frac{1}{\sqrt{N}} \left[1 + \frac{2}{N} (N-1)r \right]^{1/2} = \frac{1}{\sqrt{2}} \sqrt{1+r} \\ N_{eff} &= \left[\frac{1}{C(N)} \right]^2 = \frac{2}{1+r} \end{aligned} \quad (3.17)$$

where r is the correlation coefficient between the two adjacent sub-images.

For the proposed compounding method, correlations between all images should be considered. For the method using two subapertures, considering the transmitter and receiver translation distances between each subaperture combinations with reference to studies made by Burckhardt [1], the following results can be reached based on (3.16):

$$\begin{aligned} C(N) &= \frac{1}{\sqrt{4}} [1 + 2r_1 + r_2]^{1/2} \\ N_{eff} &= \left[\frac{1}{C(N)} \right]^2 = \frac{4}{1 + 2r_1 + r_2} \end{aligned} \quad (3.18)$$

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where, r_1 is the correlation coefficient between the two images generated by those subaperture combinations between which only the transmitter or receiver is translated with a fixed distance, for example, the subaperture combinations referred by $TSA_1 - RSA_1$ and $TSA_1 - RSA_2$, $TSA_1 - RSA_1$ and $TSA_2 - RSA_1$. r_2 is the correlation coefficient between the images generated by the subaperture combinations between which both the transmitter and receiver are translated, for example, the subaperture combinations referred by $TSA_1 - RSA_1$ and $TSA_2 - RSA_2$, $TSA_1 - RSA_2$ and $TSA_2 - RSA_1$.

Utilizing Fig. 3-3, Fig. 3-4 and equations (3.17), (3.18), N_{eff} can be computed for the subarray compounding and the proposed subaperture compounding, separately. The computation results are presented in Fig. 3-5 versus the overlapping ratio.

Fig. 3-5 N_{eff} obtained in the subarray compounding and the proposed TRSAC using two subapertures

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When the transducer array is divided into two parts, the number of compounding images is 2 in the subarray compounding, while it is 4 in the proposed subaperture compounding. In Fig. 3-5, we can see that equivalent number of independent images N_{eff} in the subarray compounding is still 2 while N_{eff} in the proposed method is about 3.25 when the two non-overlapping subapertures are divided. It shows the proposed method provides more independent images for compounding, leading to better speckle reduction results. In Fig. 3-5, we also find that with the increase of the overlapping ratio between the two overlapping subapertures, the N_{eff} curve of the proposed method is decreasing, while the curve of the subarray compounding keeps almost constant at the beginning and decreases later. The rapid decrease of N_{eff} found in the proposed method makes the curve downward and close to that in the subarray compounding. In Fig. 3-5 we can find a specific overlapping ratio before which the proposed method obtains more independent images than does the subarray compounding. At such specific overlapping level the numbers of independent images obtained by the two methods are identical, and after that overlapping level the subarray compounding acquires more number of independent images for compounding purpose. Such observations remind the study that the proposed method can give better image improvement before some specific overlapping ratio, e.g. about 0.43 in the Fig. 3-5

Fig. 3-6 presents the computation results of η in the subarray compounding and the proposed method. In Fig. 3-6, we can see that values of η in both subarray compounding and the proposed method are greater than unity when the overlapping ratio does not exceed a specific degree. This means before the specific overlapping ratio, although the lateral resolution loss exists in the two methods, they do improve the compounded images

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as speckle is efficiently reduced. From curves drawn in Fig. 3-6, η is 1.57 in the proposed method and 1.0 in the subarray compounding when the non-overlapping subapertures are employed (overlapping ratio is 0). It indicates that when speckle reduction and the lateral resolution loss are considered together, the proposed method improves image and the subarray compounding can not provide improvement, comparing with the conventional single imaging with the entire array.

Fig. 3-6 η obtained in the subarray compounding and the proposed TRSAC using two subapertures

With the increase of the overlapping ratio, the curve of η of the proposed method is dropping, while that of the subarray compounding rises first and drops later. This is because when the lateral resolution (represented by L_s/L) increases, the equivalent number of independent images N_{eff} in the proposed method decreases all along, while N_{eff} in the subarray compounding first keep constant and drops later as indicated by the Fig. 3-5. In Fig. 3-6, we can see there exists a specific overlapping ratio (0.43 also) before

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which η of the proposed method is larger than that of the subarray compounding. At this specific overlapping ratio, the two methods provide the same level of improvement. And after that, the subarray compounding gives larger incorporated improvements. Above observations indicate us that when the two non-overlapping subapertures are divided, the proposed method works better than either the subarray compounding, or the conventional single imaging with the entire transducer. When the two overlapping subapertures are employed, the proposed method also works better if the overlapping ratio is small, e.g. less than 0.43.

From above studies, conclusion can be made that although the lateral resolution loss exists in the proposed method, it improves the final image quality considering both speckle reduction and the lateral resolution, on the condition that the overlapping ratio between the subapertures is small.

3.2.5 Scan Line Steered (SLS) Technique

In compounding methods of moving the transducer laterally [20], [24], [32], the focusing area, which is in front of the transducer, is changing (see in Fig. 2-3). In previous compounding methods using subarrays [18], focusing area of a subarray is in the front of it and changes as another subarray is activated. The ever changing focusing areas makes the averaging of the compounding can be done only at the overlapping area (shadowed area in Fig. 2-3). Finding the overlapping areas in the compounding images cost additional work in most spatial compounding methods [18]. Various methods have been applied to record the spatial information related to each compounding images, which is

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used to compute the overlapping area. For example, a precisely controlled motor system was used in [8] to provide accurate step size when moving the transducer. In subarray compounding, the spatial information of the overlapping area can be derived using the parameters of the subarray [11], e.g. element contained, distance between two elements, etc.

The reason that causes the focus area changing in most spatial compounding methods is that the scan line sets, which are used to form an image later, are constructed symmetrically to the center of the active transducer in the projection plane. When compounding images are obtained by moving the transducer, the ever changing positions of the transducer leads to different scan lines to be constructed. In subarray compounding, centers of the subarrays are in different positions, causing scan line sets associated to each subarray are different from one to another. In early studies such arrangement is obvious. And another advantage of employing varying scan line sets is that it can save memory spaces to store the delay coefficients for constructing points in the scan lines. The coefficient associated to an element in the active transducer or subarray is computed using the spatial information of this element, the focusing point in the scan lines, and the subarray center. In subarray compounding, coefficients associated to each subarray are of the same set, saving the memories obviously. However, applying common delay sets among different subarrays let the subarrays generate their own scan lines (see in Fig. 3-7(a)). Therefore, the compounding images have different image content and the system has to find the overlapping areas among them to do compounding.

In this study the scan line steered (SLS) technique is proposed to generate the compounding images constructed by the same set of scan lines, even though the active

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transmit-receive subaperture combinations are changing. A set of scan lines is first set in advance symmetrically to the center of the entire transducer in the projection plane. The time delay coefficients associated to each element is then calculated using the spatial information of these preset scan lines, no matter which subapertures are activated. Through these coefficients, echoes collected by an active transmit-receive subaperture combinations are focused to construct these preset scan lines. Thus the compounding images formed from different subaperture combinations have same content and the compounding can be performed directly without the trouble of finding the overlapping area. As the scan lines of different subaperture combinations are set to identical, the time delay sets associated to each subaperture are then different, i.e. subapertures no longer share the common delay sets.

Computing the delay coefficient associated to a transducer element uses the spatial information of the element, the selected focal point in a scan line, and a referring base point. In the conventional imaging system, such base point is set as the center point of the transducer. In the subarray compounding mentioned above the base point is set to each subarray center (positions pointed by the arrows in Fig. 3-7(a)). When implement the SLS technique, delay coefficients associated to a transducer element is decided by the referring base point selected as the locations of the element and the scan lines are fixed already. Different selections of the referring base point lead to different computation results. If the reference base point is selected to be at the center of the subaperture which contains the element under computation (as the subarray compounding above), the relations among delay sets associated to the subaperture can be shown by Fig. 3-7(b) (the referring base points are indicated by the arrows). We can see that delay sets of different subapertures are no longer identical as those computed for the subarray compounding. Also we can fix

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the referring point to one place during the delay computations for all subapertures. For example, the center of the entire transducer can be selected as the referring base point for

Fig. 3- 7 Delay structures associated to subapertures in: (a) the subarray compounding with the referring base point set to the center of each subarray, and in the SLS technique with the referring base point set to (b) the center of each subaperture, (c) the center of the transducer

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all subapertures. The delays associated to subapertures are then in a structure indicated by Fig. 3-7(c). Again, the delay sets for different subapertures can be observed not identical. Considering the procedures of computing a beamforming delay, it is easily to find out that delays represented by Fig. 3-7(c) can be derived from Fig. 3-7(b) by adding some offsets. In detail, adding all delay coefficients associated to one subaperture with an offset whose value is determined by the distance from the subaperture center to the entire transducer center. If the common scan lines in the SLS technique are placed symmetrically to the center of the transducer and the referring base point is fixed to the center of the entire array, then the delay values associated to the transducer elements will be identical to those computed in the conventional imaging using the entire transducer.

3.2.6 Work Flow of the Proposed Method

Fig. 3-8 illustrates the main processing steps of the TRSAC approach using one TSA and all RSAs. In the propose TRSAC approach, subapertures are first divided in a phase array. A set of scan lines is selected in front of the transducer. Applying the SLS technique, the delay sets associated to RSAs are computed in advance and stored in memories. A TSA is selected to excite ultrasound beams and a RSA is chosen to collect echoes during the period of forming the scan lines. The active TSA and RSA can be the same subapertures or not. Echo signals received by the active RSA are amplified first to compensate the attenuation occurred during the beam travel. The amplified signals are then beamformed with the associated delay set to generate the predefined scan lines. Because ultrasound images are constructed by the amplitude of the collected echoes, the envelope detection is then performed on signals of each scan line. The acquired envelope signals are then processed to form an image. After that, the same TSA is used and another RSA is selected

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as active to generate the second image for compounding. Repeating above procedures until images from all RSAs have been constructed. Then select a new TSA as active and repeat the procedures. Compounding can be fulfilled by averaging images obtained from activating all transmit-receive subaperture combinations.

Fig. 3- 8 Illustration of the proposed spatial compounding

3.3 Simulations

3.3.1 Evaluation Parameters

Before showing the simulation results, I would like to point out that the performance of an image enhancing method is always task dependent. For example, the “best” method for imaging low-contrast lesions might not be the best way for cardiac imaging. The

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compounding method proposed here is mainly studied for suppressing speckle. It might aid the low contrast lesion detections but might decrease the output in high resolution tasks. In previous section a measure has been computed to examine the net performance of the proposed method considering the lateral resolution loss and speckle reduction simultaneously. Here two typical parameters are selected to evaluate the ability of the proposed method on speckle suppression: the speckle signal-to-noise ratio (SSNR) [22], [24], [53] and the contrast-to-noise ratio (CNR) [22], [24], [47]. They can be computed as the following:

$$\begin{aligned} SSNR &= \frac{\hat{\mu}_n}{\hat{\sigma}_n} \\ CNR &= \frac{|\hat{\mu}_s - \hat{\mu}_n|}{\sqrt{\hat{\sigma}_s^2 + \hat{\sigma}_n^2}} \end{aligned} \quad (3.19)$$

where $\hat{\mu}_s$ and $\hat{\sigma}_s^2$ are the mean and variance of the values within an object area. $\hat{\mu}_n$ and $\hat{\sigma}_n^2$ are the mean and variance of the speckle background, which is decided by the visual observations. In the following experiments, the speckle background is selected near the object. The SSNR parameter measures speckle noise reduction capacity in the selected locations and the CNR quantifies the ability of perceiving an object against the background of speckle. A good method for speckle reduction should result in relative large SSNR and CNR values.

3.3.2 Data Sets and Subaperture Combination Plans

To evaluate our compounding approach, simulations were carried out using several phantom data sets, which were obtained by the Biomedical Ultrasonics Laboratory, University of Michigan. Here we show test results with data sets of two phantoms.

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The first phantom consists of some circular cylinders of absorbing material, some cylinders of strongly reflecting material, and some metal wires at various distances from the transducer. The radio frequency (RF) data sets of the phantom were acquired with an experiment system using a transducer of 64 elements, whose center frequency is 3.33MHz. The inter-element spacing of the transducer is 0.24mm. The sampling frequency is set to 17.76MHz and the sample number is 4096 per channel.

The second phantom contains four low-resolution cysts over a speckle background. The transducer had 128 elements and its center frequency was 3.5 MHz. The inter-element spacing of the transducer is 0.22mm. The RF data sets were sampled at 13.89 MHz and 2048 samples were obtained per channel.

The ultrasound RF data sets were collected using a complete set synthetic aperture focusing technique (SAFT), i.e. the ultrasound pulse excitations and echo collections were carried out through the transducer elements one by one. Thus the focusing for transmit and receive in the ultrasound imaging can be simulated using the synthetic aperture focusing technique [47], [48], i.e. they are implemented by applying appropriate delays in the signals collected by each element. To implement the SLS technique, 180 scan lines were set before the transducer center within 90 degree beam deflection. The delays associated to each transducer element for constructing these scan lines were calculated referring to the center of the transducer (Fig. 3-7(c)). When a transmit-receive subaperture combination is active for imaging, the delays related to their elements were read from memories. In the simulations, the Hamming coefficients were applied to implement the receiving apodization.

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Two and three subapertures were divided subsequently in the transducer for simulating the TRSAC and the subarray compounding. Table 3-1 listed the representations of the subaperture combinations and the subarrays formed.

Subaperture number	2	3
Subaperture combination number/subarray number	4/2	9/3
Subaperture combinations	$TSA_1 - RSA_1$ $TSA_1 - RSA_2$ $TSA_2 - RSA_2$ $TSA_2 - RSA_1$	$TSA_1 - RSA_1$ $TSA_1 - RSA_2$ $TSA_1 - RSA_3$ $TSA_2 - RSA_1$ $TSA_2 - RSA_2$ $TSA_2 - RSA_3$ $TSA_3 - RSA_1$ $TSA_3 - RSA_2$ $TSA_3 - RSA_3$
Subarrays	$TSA_1 - RSA_1$ $TSA_2 - RSA_2$	$TSA_1 - RSA_1$ $TSA_2 - RSA_2$ $TSA_3 - RSA_3$

Table 3 - 1 Subaperture combinations and subarrays used in the simulations

3.3.3 Result Analysis

For comparisons, the conventional imaging and the subarray compounding are also simulated to construct the phantom images. The SLS is also applied to the subarray compounding to save the effort for finding the overlapping area.

3.3.3.1 Compounding with Non-Overlapping Subapertures

The number of non-overlapping subapertures used in the following simulations was set to two and three, separately. Fig. 3-9 and Fig. 3-10 contain the simulated images of the first phantom and the second phantom using two non-overlapping subapertures, respectively. The subaperture size applied in constructing images in Fig. 3-9 is 32-element and in Fig. 3-10 is 64-element, separately, according to the transducer sizes used for scanning the

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phantoms. In each figure, images of the conventional imaging using the entire array and the array whose length is equal to the subaperture are also shown. The lateral resolution loss can be found if we compare the images from the methods using partial array elements with the image from the system employs the entire array, especially in the point targets. However, in Fig. 3-9(a), (b) and Fig. 3-10(a), (b), speckle noise can be observed in the areas of the image background and the areas inside the image objects. From the compounding images in Fig.3-9 and Fig. 3-10, we can see speckle is suppressed by both the subarray compounding and the TRSAC. Compared with the images from the subarray compounding, higher degree of speckle removal can be observed in the output images of the TRSAC method, e.g. the upper center homogeneous area in Fig. 3-9 and areas inside the circular objects in Fig. 3-10. Visually, the backgrounds of the images obtained by the TRSAC method are more uniform and the objects in these images are easier to be distinguished.

CNR and SSNR parameters were calculated in the images obtained. In the simulated images of the first phantom CNR values were computed around the second lesion and the third cyst, counting from the image top to the bottom. SSNR values were calculated using the pixels inside two selected areas, which are marked in Fig. 3-9(a). Table 3-2 gives the CNR and SSNR obtained in the images in Fig. 3-9. CNR values of the proposed TRSAC are 3.65 and 2.67, which are a bit higher than those achieved by the subarray compounding of 3.57 and 2.37. CNR values gotten by the conventional imaging method using the entire array of 64 elements are 3.20 and 2.71, using 32 element array are 2.50 and 1.97. Both the TRSAC and the subarray compounding increased CNR in the lesion area. Compared with the values obtained in the subarray compounding (9.64 and 7.91), the SSNR computed in the image from the TRSAC are greatly increased

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Fig. 3- 9 Simulated ultrasound images of the first phantom using two 32-element non-overlapping subapertures on a 64 element array (a) conventional imaging of 64 element array (b) conventional imaging of 32 element array, (c) the subarray compounding, and (d) the TRSAC

Imaging methods	CNR		SSNR	
	Second Lesion	Third Cyst	Area1	Area2
Conventional imaging of 64 element	3.20	2.71	7.09	5.01
Conventional imaging of 32 element	2.50	1.97	6.80	4.88
Subarray Compounding	3.57	2.37	9.64	7.91
TRSAC	3.65	2.67	12.60	11.55

Table 3 - 2 CNR and SSNR computed in the images in Fig. 3-9

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Fig. 3- 10 Simulated ultrasound images of the second phantom using two 64 element non-overlapping subapertures on a 128 element array (a) conventional imaging of 128 element (b) conventional imaging of 64 element array, (c) the subarray compounding, and (d) the TRSAC

Imaging methods	CNR		SSNR	
	First Cyst	Second Cyst	Area1	Area2
Conventional imaging of 128 element	2.17	1.67	6.42	6.13
Conventional imaging of 64 element	1.92	1.65	6.37	6.09
Subarray Compounding	2.20	1.85	8.71	8.30
TRSAC	2.35	2.21	10.81	9.05

Table 3 - 3 CNR and SSNR computed in the images in Fig. 3-10

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(12.60 and 11.55). Compared to the conventional imaging, both of the methods increase SSNR values much.

In the simulated second phantom images, CNR values were computed around the first and second cyst areas, SSNR values were calculated inside two areas indicated in Fig. 3-10(a). The calculation results are shown in the Table 3-3. From it, we can see that the two CNR values obtained by the TRSAC (2.35 and 2.21) are a little higher than those obtained by the subarray compounding (2.20 and 1.85). The TRSAC increased the SSNR values to 10.81 and 9.05 in the two areas, which are larger than those obtained by the subarray compounding: 8.71 and 8.30.

Fig. 3-11 and Fig. 3-12 show the simulated images of the first phantom and the second phantom using three non-overlapping subapertures. At this time, the subaperture size applied for constructing the first phantom images is 21-element and for constructing the second phantom images is 42-element, separately. Among images in Fig. 3-11 and Fig. 3-12, we can observe that the images obtained by the TRSAC method have least speckle noise. Compared with images shown in Fig. 3-9 and Fig. 3-10, more lateral resolution loss can be observed but speckle is further smoothed. CNR and SSNR were computed in these images and the results are presented in the Table 3-4 and Table 3-5. The TRSAC achieved close CNR values with those obtained by the subarray compounding. But the TRSAC increased the SSNR values much larger than the subarray compounding did. Visual and quantitative comparisons show that increasing the number of subapertures used in the TRSAC leads to more improvement in the compounded images, if the correlations between the two subaperture combinations do not change. This is because enlarging the number of subapertures increases the number of images for averaging.

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Fig. 3- 11 Simulated ultrasound images of the first phantom using two 21-element non-overlapping subapertures on the 64 element array (a) conventional imaging using 64- element array (b) using 21-element array, (c) the subarray compounding, and (d) the TRSAC

Imaging methods	CNR		SSNR	
	Second Lesion	Third Cyst	Area1	Area2
Conventional imaging of 64 elements	3.20	2.71	7.09	5.01
Conventional imaging of 21 elements	2.33	1.33	6.01	5.26
Subarray compounding	3.20	2.13	12.22	12.71
TRSAC	3.22	2.07	16.08	14.75

Table 3 - 4 CNR and SSNR computed in the images in Fig. 3-11

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Fig. 3- 12 Simulated ultrasound images of the second phantom using three 42-element non-overlapping subapertures on the 128 element array (a) conventional imaging using 64-element array (b) using 42-element array, (c) the subarray compounding, and (d) the TRSAC

Imaging methods	CNR		SSNR	
	First Cyst	Second Cyst	Area1	Area2
Conventional imaging of 128 element	2.17	1.67	6.42	6.13
Conventional imaging of 42 element	1.92	1.46	6.28	5.81
Subarray compounding	2.23	1.62	10.76	9.46
TRSAC	2.46	1.95	14.45	12.84

Table 3 - 5 CNR and SSNR computed in the images in Fig. 3-12

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Other RF data sets are also tested in the developed method and got the similar results. Compared to the subarray compounding, the TRSAC achieved a little higher SNR values, while obtaining much larger SSNR values. These results show that the TRSAC is superior to the subarray compounding on suppressing speckle noise in ultrasound images without degrading the object contrast. Referring to Fig. 3-3, the correlations between the two adjacent non-overlapping subaperture combinations are nearly constant with the value of 0.25. Although this value is larger than that computed between the adjacent subarrays (which is zero), it is still of small value. Suggested by Burckhardt [2], images obtained through the adjacent subaperture combinations can be considered as ‘almost’ independent. Therefore, when non-overlapping subapertures are employed, the proposed method achieves better image improvement than the subarray compounding does because it constructs more number of images for averaging. Compared with systems employ the entire transducer array, the proposed TRSAC shows a net gain in the overall image improvement as resolution is degraded but noise is improved.

3.3.3.2 Compounding with Overlapping Subapertures

The overlapping subapertures were then divided in the transducers to verify the TRSAC performance on enhancing ultrasound image qualities. In the following simulations, two overlapping subapertures were used. To test the TRSAC capability under varying overlapping ratios, we formed images with fixed subaperture sizes but changing the overlapping sizes between the two adjacent subapertures. With the constant subaperture size the lateral resolution obtained in the compounding does not change. However, the transducer sizes reduce with the increasing of the overlapping sizes. In the simulations using the first phantom data, each of the two overlapping subapertures contains 32

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elements and the overlapping sizes increased from 4 to 24 steadily. Table 3-6 listed the overlapping sizes applied in simulating the TRSAC with the first phantom data. It also contains the correspondent overlapping ratios, the correlation coefficients between the adjacent subaperture combinations (with the Hamming coefficients as the receive apodization), the transducer sizes needed, and the correlations between the adjacent subarrays.

subaperture number	2	Subaperture elements				32
Overlapping elements	4	8	12	16	20	24
Transducer elements	60	56	52	48	44	40
Overlapping ratio	0.13	0.25	0.38	0.5	0.63	0.75
Correlations between the adjacent subaperture combinations	0.25	0.36	0.50	0.64	0.78	0.89
Correlations between the adjacent subarrays	0.0	0.0	0.05	0.15	0.37	0.63

Table 3 - 6 Information for dividing two 32-element overlapping subapertures on the transducer scanning the first phantom

From Table 3-6, we can see that as the overlapping size increases, the correlation between the two adjacent subaperture combinations rises steadily, while the transducer size decreases without deteriorating the lateral resolution. Hence, increasing the overlapping size will degrade the compounding improvement, but it will save the cost of making a long transducer.

Fig. 3-13 show the simulated images of the TRSAC and the subarray compounding with the overlapping size of 8. The overlapping ratio is then 0.13. The conventional 32-element and 64-element imaging results are also shown for a reference. In Fig. 3-13, we

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can see that both methods have speckle suppressed compared to the conventional imaging: the background looks smoother and the objects are easier to be perceived. The proposed TRSAC reduced more speckle than the subarray compounding did, e.g. in the left bottom of the compounded images. Table 3-7 contains the CNR and SSNR values computed in the selected areas in the images obtained. Among the three methods, the TRSAC gives the largest evaluation parameters. Referring to the CNR values achieved by the conventional imaging, which are 2.50 around the second lesion and 1.97 around the third cyst, the new TRSAC increased them to 3.51 and 2.47, separately. They are slightly larger than the CNR values obtained by the subarray compounding (3.45 and 2.36). The SSNR obtained by the TRSAC and the subarray compounding in the first area are 11.85 and 9.53, respectively. In the second area, the TRSAC increased the SSNR to 10.66 and the subarray compounding increased it to 7.86. In both areas, the TRSAC improved SSNR larger than the subarray compounding did. The simulation results indicate that when the overlapping size is 8, the TRSAC method has better performance on reducing speckle noise compared to the subarray compounding.

Fig. 3-14 shows the simulated images of the TRSAC and the subarray compounding with the overlapping size between subapertures was set to 20. The overlapping ratio is then computed as 0.63. Although the image generated by the TRSAC has better quality than the conventional imaging, visually it has similar quality as the image formed by the subarray compounding. The CNR and SSNR values obtained by the two methods are shown in the Table 3-8. The CNR values achieved by the TRSAC are 3.12 and 2.18 around the two objects. They are a little smaller than the CNR obtained by the subarray compounding. The SSNR in the image generated by the TRSAC are 9.13 and 7.59, which are quite close to the values obtained by the subarray compounding: 9.05 and 7.48.

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Fig. 3- 13 Simulated ultrasound images of the first phantom using two 32-element 8-overlapping subapertures on the 64 element array (a) conventional imaging using 64 element array (b) using 32-element array, (c) the subarray compounding, and (d) the TRSAC

Imaging methods	CNR		SSNR	
	Second Lesion	Third Cyst	Area1	Area2
Conventional imaging of 64 elements	3.20	2.71	7.09	5.01
Conventional imaging of 32 elements	2.50	1.97	6.80	4.88
Subarray compounding	3.45	2.36	9.53	7.86
TRSAC	3.51	2.47	11.85	10.66

Table 3 - 7 CNR and SSNR computed in the images in Fig. 3-13

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Fig. 3- 14 Simulated ultrasound images of the first phantom using two 32-element 20-overlapping subapertures on the 64 element array (a) conventional imaging using 64- element array, (b) using 32-element array, (c) the subarray compounding, and (c) the TRSAC

Imaging methods	CNR		SSNR	
	Second Lesion	Third Cyst	Area1	Area2
Conventional imaging of 64-element	3.20	2.71	7.09	5.01
Conventional imaging of 32-element	2.50	1.97	6.80	4.88
Subarray compounding	3.18	2.29	9.05	7.48
TRSAC	3.12	2.18	9.13	7.59

Table 3 - 8 CNR and SSNR computed in the images in Fig. 3-14

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Through visual and quantitative evaluations, we can see that when the overlapping size is increased to 20, the TRSAC has similar speckle reduction ability as the subarray compounding.

Besides 8 and 20, subapertures with other overlapping sizes listed in the Table 3-4 were also applied in the simulations subsequently to test the TRSAC performance. CNR and SSNR were calculated in the images constructed by the TRSAC and the subarray compounding. The curves of CNR and SSNR versus the subaperture overlapping ratio are shown in Fig. 3-15. We can see that the CNR and SSNR curves obtained by both methods decrease when the subaperture overlapping ratio enlarges. This is because the increasing of the overlapping elements makes the subaperture combinations (or the subarrays) more correlated, which will reduce the compounding effect. From the curves we see that the TRSAC has larger CNR and SSNR values than the subarray compounding when the subaperture overlapping sizes are small. It means the TRSAC has better speckle reducing capability in such conditions. As the overlapping element increases, CNR and SSNR curves of the TRSAC decreases gradually to the curves of the subarray compounding, representing the two methods are providing similar speckle suppression degrees. With the further growth of the overlapping sizes, the TRSAC obtained less CNR and SSNR values than those acquired by the subarray compounding. It indicates that less improvement achieved by the proposed method when the subaperture overlapping size grows large. Such changes can be explained as the following. As we know, the number of the compounding images and the correlations between them are the two factors deciding the compounding effect. Although images constructed by the TRSAC are more correlated than those formed by the subarray compounding, the TRSAC generates more number of

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Fig. 3- 15 CNR and SSNR values obtained in the compounded images of the first phantom using two overlapping 32-element subapertures: (a) CNR around the second lesion; (b) CNR around the third cyst; (c) SSNR of the area 1, and (d) SSNR of the area 2. The overlapping size is increasing from 4 to 24

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images for averaging. Initially when the overlapping elements between the subapertures are small, the individual images used by the TRSAC are low correlated and the compounding image number plays a role of more importance. Therefore, the TRSAC achieves better speckle suppression result than the subarray compounding does. With the subaperture overlapping size growing large, the increasing image correlations imposed more negative impacts on the proposed TRSAC method because they are closer to 'high correlations'. Then the performance of the proposed method downgrades at a faster speed and approaches to that of the subarray compounding. At a specific overlapping degree, the image correlations in the TRSAC method reach a level high enough to counteract the positive impact brought by the larger image number, resulting in the equal performance of the two compounding methods. After that, the correlations among the compounding images obtained in the TRSAC method are so high that the compounding effect is heavily decreased. In this condition, although the proposed method generates more images for compounding, it provides fewer image enhancements than the subarray compounding. In Fig. 3-15 we can find the critical overlapping degrees (represented by the overlapping ratio) in the CNR curves are 0.52 and 0.46, separately. In the SSNR curves they are both around 0.65. Comprehensively, we can consider that the overlapping limit for using the RF data of the first phantom is 0.65, as we consider speckle reduction mainly in this study. Before it, the TRSAC method reduces more speckle than the subarray compounding.

The TRSAC method is then tested using the RF data of the second phantom. Two overlapping subapertures were divided in the transducer scanning the phantom. Each of them contains 64 elements and the subaperture overlapping size is increased from 4 elements to 52 elements gradually.

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Fig. 3-16 presents the compounded images from the TRSAC and the subarray compounding with 8 elements as the overlapping size. The overlapping ratio is then 0.13. Speckle suppression can be observed in the images obtained by the two methods. The TRSAC reduced more speckle noise than the subarray compounding did, e.g. in the image background. The CNR and the SSNR, which were calculated in the selected areas as those used in previous tests, are presented in the Table 3-9. As the TRSAC achieved larger SSNR and CNR than the subarray compounding, it has stronger ability on reducing speckle noise without decreasing the object contrast.

Fig. 3-17 shows the simulated images from the TRSAC and the subarray compounding applying 40-element overlapping between the two subapertures. At this time, the two images from the methods are similar, both in speckle suppression degree and object contrast enhancements. Table 3-9 contains the CNR and the SSNR calculated in the output images. The SSNR in the image obtained by the TRSAC are 8.22 and 7.89. And in the subarray compounding they are 8.26 and 7.92. The close SSNR values indicate that when the subaperture overlapping elements reaches 40, the TRSAC has the similar ability on reducing speckle as the subarray compounding. The overlapping ratio in this condition is 0.63.

The compounding simulations with other subaperture overlapping sizes were carried out using the RF data of the second phantom. In each image obtained, the CNR and SSNR in the selected areas were computed. The curves of CNR and SSNR to the subaperture overlapping ratio were drawn in the Fig. 3-18. In the figure, we can obtain the similar results as those found in the Fig. 3-15. The CNR and SSNR obtained by the TRSAC and the subarray compounding decrease when the subaperture overlapping ratio increases,

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Fig. 3- 16 Simulated ultrasound images of the second phantom using two 64-element 8-overlapping subapertures on the 128 element array (a) conventional imaging using 128-element array, (b) using 64-element array, (c) the subarray compounding, and (d) the TRSAC method

Imaging methods	CNR		SSNR	
	First Cyst	Second Cyst	Area1	Area2
Conventional imaging of 128 element	2.17	1.67	6.42	6.13
Conventional imaging of 64 element	1.92	1.65	6.37	6.09
Subarray compounding	2.19	1.88	8.71	8.27
TRSAC	2.31	2.16	10.40	8.87

Table 3 - 9 CNR and SSNR computed in the images in Fig. 3-16

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Fig. 3- 17 Simulated ultrasound images of the second phantom using two 64-element 40-overlapping subapertures on the 128 element array (a) conventional imaging using 128-element array, (b) using 64-element array, (c) the subarray compounding, and (d) the TRSAC method

Imaging methods	CNR		SSNR	
	First Cyst	Second Cyst	Area1	Area2
Conventional imaging of 128 element	2.17	1.67	6.42	6.13
Conventional imaging of 64 element	1.92	1.65	6.37	6.09
Subarray compounding	2.10	1.77	8.26	7.92
TRSAC	2.08	1.87	8.22	7.89

Table 3 - 10 CNR and SSNR computed in the images in Fig. 3-17

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Fig. 3- 18 CNR and SSNR values obtained in the compounded images of the second phantom using two overlapping 64-element subapertures: (a) CNR around the first cyst; (b) CNR around the second cyst; (c) SSNR of the area 1, and (d) SSNR of the area 2. The overlapping size is increasing from 4 to 52

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representing degraded speckle reduction ability. In the conditions where the overlapping ratio are small, the images outputted by the TRSAC have larger CNR and SSNR than those obtained by the subarray compounding; Following with the increase of the overlapping ratio, the decreasing speed of the CNR and SSNR obtained in the images from the TRSAC is more rapid, causing the speckle reduction ability of the TRSAC to approach that of the subarray compounding. In a specific overlapping ratio, the TRSAC and the subarray compounding have the same speckle suppression level, at which the CNR and SSNR curves of the TRSAC go across with the curves of the subarray compounding. After that, the CNR and SSNR achieved by the TRSAC are less than the subarray compounding. In Fig. 3-18, the CNR values computed in the TRSAC images around the second cyst are always larger than those computed in the images formed by the subarray compounding. The critical overlapping ratios in other three curves can be observed as 0.54, 0.62, and 0.62, separately. Therefore, the final critical overlapping ratio for compounding using the second phantom RF data can be set as 0.62. Below this level the TRSAC removes more speckle than the subarray compounding does. This is approximate to the observations obtained in the previous simulations using the RF data of the first phantom.

The compounding simulations with various subaperture overlapping ratios have also been done using the RF data sets of other phantoms. The similar results as above have been gotten. Therefore, I can conclude that when the overlapping subapertures are employed, the proposed TRSAC method has better speckle reduction ability than the subarray compounding, on condition that the subaperture overlapping ratio is not large. Less than 0.5 is suggested if some obvious improvements want to be achieved compared to the subarray compounding.

3.4 Considerations on Implementing the TRSAC

The processing structure of a typical medical ultrasound imaging system with a phased array of K elements is shown in Fig. 3-19(a). The K array elements of the transducer are active at the same time for ultrasound transmitting and receiving. As we known, a short acoustic pulse is generated through the transducer, focused at a distance. The echoes reflected by the tissue structures are collected by the entire array elements and then amplified, filtered, and sampled in a digital imaging system at a frequency higher than the Nyquist frequency. The sampled signals from each channel are then delayed by a set of associated times and summed to form a focused scan line. The current line of the final image for display is composed of the decimated envelope signals of the delay-sum echoes. Other image lines can be obtained by repeating the procedures with different delay sets. The final output image is a matrix of dimensions $S \times L$, where S is the number of decimated samples and L is the number of the scan lines required.

The basis of the SLS-TRSAC is to divide several subapertures in the transducer array and select one for transmitting, one for receiving at a time. The subaperture number is assumed to be as N and each of them contains M transducer elements ($M < K$). Each subaperture has its own set of beamforming delays in order to steer the receiving echoes to the common scan lines predefined. In the transmit stage, only one subaperture can be active in the TRSAC. Thus, the pulse generation circuits can be time shared among the subapertures. As indicated in the Fig. 3-19(b) and (c), only elements in the subaperture which are scheduled to be active are connected to the pulse generation circuits. The RSA processing can be realized in two ways. One is shown in Fig. 3-19(b), adopting the same structure as that used in the transmit stage – time sharing the receiving circuits among the

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Fig. 3- 19 Processing of the medical ultrasound: (a) traditional processing, (b) the TRSAC with time shared transmit and receive circuits, (c) the TRSAC with time shared transmit circuits and several sets of receive circuits for each of the subaperture.

RSAs with the help of multiplexers. The delay set of the circuits changes when different subapertures are active for receiving. Another way is shown in Fig. 3-19(c), providing each RSA a set of receiving circuit. A circuit set has its own delay set associated to the correspondent receive subaperture. Hence, the transmit circuits can be saved in some extent compared with the conventional imaging system, depending on the subaperture sizes divided. The two way of implementing the receive subaperture processing have

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different properties. The receiving circuits can also be saved if we share them among the receive subapertures. But the time for collecting all of the images for compounding is lengthened and the frame rate is reduced. In the second way, we need more processing units to handle the echo signals from each RSA simultaneously. The advantage of the second implementation is that all compounding images from the same transmit subaperture can be obtained simultaneously and the frame rate loss can be saved greatly compared with the first implementation way.

Like other spatial compounding methods, the TRSAC requires multi images for averaging. It reduces the frame rate and may not meet the requirements of the real-time imaging. To solve the problem, two implementations can be found in Fig. 3-19 (b) and (c), separately, according to the two ways of realizing the receive subaperture processing. As shown in Fig. 3-19(b), each transmit-receive subaperture combination is allocated a block of memory for temporarily storing the images from it. N^2 such memory blocks are needed in a total. The system outputs the compounded image by averaging all images stored in the temporary memory blocks. When a new image is generated from one transmit-receive subaperture combination, the content in the corresponding memory block is replaced by it. And the system updates the output as soon as the replacement finishes. In Fig. 3-19(c), N envelope images are generated simultaneously. The TSA associated with each of them is the same. These images are averaged and then temporarily store the result into a memory block assigned to the TSA. Therefore, N such temporary memory blocks are required corresponding to the number of TSAs. The compounded image is the average of these temporary stored results. At the time one TSA finishes its firing, the old image in the relative memory block is replaced by the new averaging result. The output compounded

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image is then updated after the replacement. Through both methods, we can recover the reduced frame rate and implement the proposed compounding in real-time.

3.5 Conclusions

In this chapter, a new spatial compounding approach, the TRSAC, is discussed. In this method, the transducer array is divided into several subapertures. In each imaging turn, one subaperture is selected for transmitting ultrasound pulses and one is for collecting echoes. The TSA and RSA being active may not be the same. This is different with those methods applying subarrays. In the new approach, each TSA and RSA combination represents a distinct assemble of angles in ultrasound pulse excitations and echo collections. The spatial information contained in the echo signals is then different from one subaperture combination to another. Speckle patterns in the images obtained by processing echoes from different subaperture combinations are partially correlated and can be reduced by compounding. Through applying subaperture combinations, the number of images can be used in compounding is increased from N to N^2 , where N is the number of subapertures/subarrays divided.

In previous subarray compounding methods, the images from each subarray consists of a set of scan lines which are distributed along the center of the subarray. It allows subarrays to share a same set of beamforming delays. But it causes spatial information of the images are different from one subarray to another. Before compounding we have to find the overlapping area to avoid the averaging error. In the new method, SLS technique is applied to form an invariable imaging area even though different subaperture combinations are activated. A set of scan lines are predefined in the projection plane of

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the transducer. Beamforming delays associated with an element of a subaperture are then calculated based on the distances from the element to the specific samples on such predefined scan lines. In this way, although the delay sets associated to RSAs are different, the scan lines formed are steered to the predefined ones. Hence, images generated by activating different subaperture combinations are with the same scan lines and can be used in averaging directly. The time for finding the overlapping area for compounding is saved then.

Two types of the subapertures can be divided in the transducer array: non-overlapping and overlapping. The non-overlapping subapertures do not allow same elements occurring in the different subapertures while the overlapping subapertures permit. The correlations between the adjacent non-overlapping subaperture combinations keep almost constant at a value of 0.25. The overlapping subaperture combinations have larger correlations, which will increase when the overlapping size grows. The advantage of employing overlapping subapertures is that we can implement the compounding with a smaller transducer without reducing the lateral resolution, compared with the transducer size on which the same number of non-overlapping subapertures is divided.

The proposed compounding loses the lateral resolution in some extent as it employs part of the transducer in ultrasound casting and receiving. However, it improves image quality by removing speckle efficiently. A measure introduced by O'Donnell, etc. is computed to evaluate the incorporated result of the proposed compounding, combining lateral resolution loss and speckle reduction. The computation results pointed out that the proposed compounding has a net gain on image improvement if the overlapping ratio is not very large (overlapping ratio is 0 among non-overlapping subapertures).

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Simulation results using the two phantom data show the speckle reduction efficiency of the TRSAC method. Both visual observations and evaluating parameters proved that the new compounding approach has better image improvement ability than the subarray compounding, when non-overlapping subapertures are applied. Simulation results showed that when the overlapping size is small, the proposed method with overlapping subapertures smoothes more speckle than the subarray compounding. As the overlapping ratio increases, the performance of the new approach downgrades toward to that of the subarray compounding. If the overlapping size keeps increasing, the proposed method achieves less image improvement than the subarray compounding. Therefore, when the proposed method is applied to enhance the ultrasound images with overlapping subapertures, the overlapping ratio is suggested to be not very large, e.g. below 0.5, if obvious improvement is hoping to be achieved than the subarray compounding.

When the subaperture number increases, the correlation coefficients between individual non-overlapping subaperture combinations do not change. As the available number of the compounding images generated by the proposed method is proportional to the square of the number of subapertures, increasing non-overlapping subaperture number will cause the speckle suppression capacity of the proposed method rising fast. However, to keep the lateral resolution unaffected, the transducer much larger than that used in the conventional imaging system has to be employed. Thus the selection of using overlapping or non-overlapping subapertures depends on the transducer cost the users can support and the image quality the users can accept.

Chapter 4

Multiscale Speckle Reduction Combining Edge Enhancement and Noise Removal

4.1 Introduction

Speckle reduction plays an important role on enhancing medical ultrasound image qualities. Compounding and filtering are the two techniques often applied for smoothing speckle images. The filtering methods analyze and process image pixels to remove speckle and preserve image details at the same time. Comparing to the compounding methods, it has the following advantages. First, filtering focuses on processing images formed. It does not require special transducer (including enlarged transducer) or beamforming technique to form specific images, which is needed by most compounding methods, e.g. the subarray compounding [18], the proposed TRSAC, and the MACI [19]. Second, unlike compounding methods which use multi images, filtering processes the image currently formed. Therefore it has little motion blur in the output image, even if the tissue moves fast. Third, since filtering methods can be implemented in software codes in modern micro processors, it is easy to develop and integrate a filtering method in ultrasound scanners. As an independent technique, filtering can be implemented in an ultrasound imaging system without compounding for suppressing speckle. It also can be

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integrated at stages following the compounding as an additional method which provides further image enhancement.

Following by the rapid progress of the digital image processing methods and the modern computer technology, developing speckle filters to improve images in diagnostic ultrasound and remote sensing are receiving more and more interests. Various filtering methods have been introduced to suppress ultrasound speckle [51] – [71], from the simple median filter to the complex adaptive filters, such as the Lee filter [56] and the AWMF [52]. A good speckle filter requires proper performances on speckle reduction and detail preservations according to the area features. In general, a strong filtering is needed in homogeneous areas because they contain fully developed speckle, while point targets and edges should be saved. And in textured areas where speckle is partially developed, a compromise between noise reduction and feature savings should be achieved [59], [93].

Most speckle filters work on a single representation of the image. The problem of such single-scale speckle filters is that they have difficulty on discriminating signal details from speckle [100]. Therefore, filtering in multiscale representations of an image is applied by several researchers to smooth speckle. These filters decompose a speckle image into several resolution representations and apply smoothing in each resolution layer. Wavelet transform [99]-[103], [107]-[109] is a common way to decompose images into multiscale representations. Only a few researchers applied pyramid decomposition [75], [76] in speckle images. In the work presented in [75], a binary edge mask is generated from an interpolated layer using specific edge detectors and used to determine whether the pixel values in the correspondent detail layer should be maintained or cleared. The limitation of the method lies in the difficulty of selecting a proper threshold to

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generate an accurate edge mask. A large threshold will lose faint edges while a small one can not give sufficient noise suppression. Furthermore, as information in detail layers is either preserved or cleared to zero, wrong edge detections may cause important detail loss in the reconstructed image. Bruno, et al, defined a modified Laplacian Pyramid (LP) structure by replacing the subtracting operation with the ratio operation when generating LP layers [76], [77]. The Kuan adaptive filter [58] was then applied to smooth each LP layer for noise reduction. The drawback of the method is that one needs to select an area supposed containing fully developed speckle to compute a reference parameter used by the Kuan filter. The selection greatly affects the performance of the method and mainly depends on the operators' experience.

In this chapter, a multiscale image processing method to suppress speckle in ultrasound images is proposed. The LP is selected as the method to decompose a speckle image because it provides access to structures of intermediate sizes and can be implemented easily. Additionally, the LP decomposition has an advantage that the boundary of an object is easier to be detected in the low resolution layers because the noise variance is lower [76]. Utilizing this, measures are taken by us to change the filters performances when different LP layers are processed on. In general, more edge enhancement and less noise removal are carried out by the filters at the lower resolution LP layers, while at the higher resolution layers the filters concentrate on noise suppression in stead of edge savings. To suppress speckle and enhance image details simultaneously, filters combining edge enhancement and noise smoothing are applied in this multiscale smoothing scheme. Three different filters were studied. The first two are edge enhancers which can remove noise at the same time: the lower-up-middle (LUM) filter [87], and the weighted majority of samples with minimum range - median (WMMR-MED) filter [88]. The third filter

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applied the fuzzy network structure based on the method proposed in [89]. It was composed by one smoothing network and one sharpening network.

The chapter is organized as follows. First, a brief introduction on LP decomposition is presented followed by the discussion of the different filters used: the LUM filter, the WMMR filter and the fuzzy network filter. The new pyramid filtering scheme is then described. Experiment results, using synthetic images, phantom images, and *in vivo* data of a human liver are also shown in the chapter. Comparisons among the new method and several other filters are presented. At the end of this chapter, conclusions and discussions on the proposed method are presented.

4.2 Pyramid Filter Scheme Design

A pyramid representation of an image is a hierarchical structure containing successively condensed information. Each layer of the pyramid represents a successively lower resolution representation of the image. The difference between the two adjacent layers is the detail information at that layer. There are a few pyramid decomposition methods have been developed. The Laplacian pyramid is chosen in this study to develop the new filtering scheme because of its simple structure and easiness to implement.

4.2.1 Laplacian Pyramid Decomposition

The Laplacian Pyramid was first introduced by Burt, et al, [21] for compressing images in 1983. Since then, it was widely used in the area of image processing, including noise cancellation [73], [74], [82] – [85]. The Laplacian pyramid can be obtained through the

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Gaussian Pyramid (GP) [72] directly, which are generated through low-pass filtering and decimating by a factor of 2 at each resolution layer. The low-pass filter is to avoid heavy aliasing which may occur in decimation and can be of half-band or not [76], [79]. The GP generation can be defined using the following equation:

$$\begin{aligned} G_k &= (\downarrow 2)[h_r(n_1, n_2) \otimes G_{k-1}] \\ G_0 &= I(m, n) \end{aligned} \quad (4.1)$$

where, $I(m, n)$ is the input image, G_k represents the GP at the layer of k , for $k = 1, 2, \dots, K$. $h_r(n_1, n_2)$ is a two-dimensional (2-D) low-pass filter for resolution reduction, which can be separated into two independent one-dimensional (1-D) low-pass filters. The frequency response of $h_r(n_1, n_2)$ is represented by $H_r(z_1, z_2)$. $\otimes$ means convolution, and $(\downarrow 2)[.]$ represents decimating by the factor of 2. Therefore, as the GP layer index k increases, its resolution and frequency components will decrease.

After generating the GP of each scale, we can obtain the LP by doing subtractions between the two adjacent GP layers. Because the higher layer GP has less resolution than the lower one, we need to interpolate the higher GP by 2 and low-pass filter the expanded GP before subtraction. The LP generation can be described using the following equation:

$$\begin{aligned} \tilde{G}_k &= h_e(n_1, n_2) \otimes (\uparrow 2)[G_k] \\ L_k &= G_{k-1} - \tilde{G}_k \\ L_K &= G_K \end{aligned} \quad (4.2)$$

where L_k is the LP at the k^{th} level, $\tilde{G}_k$ is the expanded GP from G_k . $h_e(n_1, n_2)$ is a 2-D low-pass filter for resolution expansion. The frequency response of $h_e(n_1, n_2)$ is

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represented by $H_e(z_1, z_2)$. $(\uparrow 2)[.]$ represents interpolating by 2. Because the GP contains low frequency content, the generation of LP can be considered as that the input image is filtered through a bank of band-pass filters. Therefore, each LP contains information within a specific frequency range. The low-pass filters $h_r(n_1, n_2)$ and $h_e(n_1, n_2)$ used in resolution reductions and expansions are independent [78]. They can be the same except that the amplitude of $h_e(n_1, n_2)$ should be two times the amplitude of $h_r(n_1, n_2)$. Two examples of the low-pass filter can be found in [73] and [76]. Getting the LP at all resolutions, a perfect reconstruction of the original image can be obtained by interpolating the low-layer GP and adding it to the LP in the upper level. It is an inverse processing of the equation (4.2). For processing ultrasound images, LP with four to five layers are enough as the image sizes are less than 512 by 512 commonly. Fig. 4-1 shows the four level 2-D LP decomposition and reconstruction.

Fig.4- 1 Illustration of four level LP decomposition and reconstruction

4.2.2 The LP Filtering Scheme

At each LP layer image details and noise of different frequency bands are contained. Speckle reduction can be expected if the noise in each LP layer is smoothed. In the Satter's method [75], edge preservations and noise rejection were implemented by multiplying pixels at each detail layer with a binary mask. In the new filtering scheme, a filter integrating an edge sharpener and a noise smoother was applied to processing all the LP layers. As each LP layer contains image details of a specific frequency range, it can provide enough information to guide filtering without damaging the important edges. Therefore, the proposed method filters each LP layer without referring to the GP at the same layer. The modified LP reconstruction procedure which integrates the filter for noise smoothing and edge enhancement at the same time is shown in Fig.4-2.

Fig.4- 2 Illustration of the proposed LP filtering scheme which combines noise reduction & edge enhancement

4.2.3 Filters Employed in the Proposed Pyramid Filtering Scheme

Edges hold a significant portion of the information in images and they are often corrupted in a noisy image. Many filters have been developed to smooth noise but few of them can enhance edges at the same time [87]. For example, a median filter with a large moving window is efficient on removing impulses, but it tends to reduce edge gradients. Linear sharpeners can increase edge gradients but they are sensitive to noise and outliers. To achieve speckle reduction without damaging important image details, three filters which integrate a noise canceller and edge enhancer are applied in our pyramid filtering approaches. They are the lower-up-middle (LUM) filter [87], the weighted majority of samples with minimum range (AWWM) filter [88] and the fuzzy network used in [89] with a modified structure.

The LUM filter and the AWWM filter are of median filter class. They have good noise smoothing ability and simple structure. Before introducing the two filters, we first give a definition used. Considering a given input data set $\{x_1, x_2, \dots, x_n\}$, its sorted version is written as $\{x_{(1)}, x_{(2)}, \dots, x_{(n)}\}$, which satisfies the following:

$$x_{(1)} \leq x_{(2)} \leq \dots \leq x_{(n)} \quad (4.3)$$

4.2.3.1 The lower-up-middle (LUM) filter

The LUM filter [87] has two controlling parameters: one for smoothing and another for sharpening. The noise suppression level can be varied from no filtering to that of the median by changing the smoothing parameter. This balances the LUM filter's

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performance between the maximum noise reduction and detail preservation. The sharpening parameter controls the amount of enhancement provided by the LUM filter. Compared with other linear techniques for edge enhancement, the LUM filter does not cause any overshoot or undershoot [87]. It can be insensitive to the additive noise when enhancing edges if the sharpening parameter is configured properly. As it has two independent parameters, the LUM filter can be configured as a smoother, a sharpener, or both at the same time depending on parameter selections. The output of LUM filter can be expressed as the following:

$$y_{LUM}(x^*) = \begin{cases} x_{(k)} & \text{if } x^* < x_{(k)} \\ x_{(l)} & \text{if } x_{(l)} < x^* \leq t \\ x_{(N-l+1)} & \text{if } t < x^* < x_{(N-l+1)} \\ x_{(N-k+1)} & \text{if } x_{(N-k+1)} < x^* \\ x^* & \text{otherwise} \end{cases} \quad (4.4)$$

where, N is the total number of pixels in the filter window, x^* is the center pixel of the moving window, t is the midpoint between $x_{(k)}$ and $x_{(l)}$. The parameter k and l are the two tuning parameters, controlling the filter's performance on smoothing and sharpening, separately. They should satisfy:

$$1 \leq k \leq l \leq (N+1)/2 \quad (4.5)$$

If $k = l = (N+1)/2$, the output of the LUM filter is simply the median of the filter window. In the case where $l = (N+1)/2$ and k is changing, the LUM filter functions as a noise smoother. Larger value of k will lead to more smoothing. And when $k = 1$ and l varies, the LUM filter is an edge sharpener. Decreasing l leads to an increased edge enhancing effect. When $1 < k \leq l < (N+1)/2$, sharpening and smoothing can be achieved

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simultaneously. Increasing k can improve the ability on noise reduction while decreasing l results in more edge enhancement. When the LUM filter is applied in our pyramid smoothing scheme, its smoothing parameter k and enhancing parameter l are adjusted at each pyramid level to give proper level of noise reduction and edge enhancement.

4.2.3.2 The weighted majority of samples with minimum range (WMMR) filter

The WMMR filter [88] also enhances edges and reduces noise at the same time. It selects the $(N + 1)/2$ most closely spaced samples inside the filter window of size N . In other words, a specific index number (l) of the ordered samples must be found such that the difference between the $x_{(l)}$ and $x_{(\frac{N-1}{2}+l)}$ researches minimum. The selected values are then multiplied by the weights associated with them. The output of the WMMR filter is the sum of the weighted values.

The WMMR filter can be represented by using the following equation:

$$y_{WMMR} = \sum_{i=l}^{\frac{N-1}{2}+l} w_i x_{(i)} \quad (4.6)$$

where w_i is the weight assigned to the i^{th} selected sorted sample. The weights decide the performance of the WMMR filter. Two different sets of weights can be found in the least median of squares filter [90] and the Shorth filter [91], which are of the WMMR filter class. Each of them has the ability to smooth noise and preserve edges simultaneously. The WMMR filter enhances edges of the image if the weights are selected as symmetrical, positive and normalized [88]. A specific filter referred as the WMMR-MED filter can be obtained if the median of the selected ordered samples is set as the output:

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$$y_{WMMR-MED}(x^*) = median\{x_{(l)}, x_{(l+1)}, \dots, x_{(\frac{N-1}{2}+l)}\} \quad (4.7)$$

Its associated weights of the selected samples can be considered as the following:

$$w_i = \begin{cases} 1 & \text{if } i = (N-1)/4 + l \\ 0 & \text{otherwise} \end{cases} \quad (4.8)$$

The WMMR-MED filter has the ability to sharpen edges and reduce noise at the same time. It can be used recursively on the input image, leading to more improvements. The dimension of the filter window also influences the filter's performance. The 2-D moving window is often used for noise reduction and edge preservation. If edge enhancement and noise smooth is the major concern, 1-D filter window is recommended. The WMMR-MED filter is applied by us in the pyramid smoothing method because of its simple structure. The dimension and the parameter l are varying at different resolution layers to achieve the best performance on noise reduction and detail preservations.

4.2.3.3 The Fuzzy Networks

A new nonlinear method which combines edge sharpening and noise reduction was developed by Russo [89]. The method adopts two fuzzy networks, one for noise smoothing and another for sharpening. The basic structure of a fuzzy network operation using a 3x3 window can be illustrated using the Fig. 4-3.

Fig.4- 3 Basic structure of a fuzzy network operation using a 3x3 window

The network contains two sub-networks, in which two classes of fuzzy set-based operations are computed based on the differences between the center pixel $x_{i,j}$ and its eight neighbors. The fuzzy set-based operations are denoted in the Fig. 4-3 as small square boxes using the symbol of $\mu_{R_i}(u, v, \alpha)$. They can be computed using the following equation:

$$\mu_{R_i}(u, v, \alpha) = \begin{cases} \max[0, 1 - \frac{|u - v - \alpha|}{2\alpha}], & i = 1 \\ \max[0, 1 - \frac{|u - v + \alpha|}{2\alpha}], & i = 2 \end{cases} \quad (4.9)$$

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Adding together all the fuzzy set-based operations inside each sub-network, we have two results. The output of the fuzzy network can then be computed using the two summation results from the sub-networks as the following:

$$\Delta x_{i,j} = \frac{K\alpha}{N} \left[\sum_{x_{m,n} \in Z} \mu_{R_1}(x_{i,j}, x_{m,n}, \alpha) - \sum_{x_{m,n} \in Z} \mu_{R_2}(x_{i,j}, x_{m,n}, \alpha) \right] \quad (4.10)$$

Where, Z is the pixel assemble $\{x_{m,n}\}$ contained by the window excluding the center pixel $x_{i,j}$. N is the size of the assemble Z , i.e. the number of pixels in Z . α is a parameter representing relations in the fuzzy set-based operation. When it is large, the fuzzy relation of u and v can be represented by “ u is far to v .” And when α is small, the fuzzy relation of u and v becomes “ u is close to v .” K is an amplifying coefficient.

Typically, K is set to 1 for noise smoothing. In this case, the network output of the equation (4.10) can be considered as an estimate of the noise amplitude [89]. Therefore, the noise-free signal $y_{i,j}$ corresponding to the original value $x_{i,j}$ can then be estimated by subtracting the network output from $x_{i,j}$:

$$y_{i,j} = x_{i,j} - \Delta x_{i,j} \quad (4.11)$$

Varying the value of α in the equation (4.10) changes the fuzzy relation estimation and leads to different noise smoothing level. Generally, a large α can be used to increase the amount of noise reduction at the cost of introducing detail blur.

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If we consider the sharpening as the opposite procedure of the smoothing, we can obtain the sharpening effect by selecting larger amplifying coefficient K and add the fuzzy network output to the original pixel value $x_{i,j}$:

$$y_{i,j} = x_{i,j} + \Delta x'_{i,j} \quad (4.12)$$

Generally, more edge sharpening effects can be obtained if we increase the value of K .

A noise smoothing network and a sharpening network were integrated by us to construct the filter for LP filtering. Its structure is illustrated in Fig. 4-4.

Fig.4- 4 Illustration of the structure of the modified fuzzy network which combines a smoothing sub-network and a enhancing sub-network

A filter combining edge enhancement and noise reduction can then be expressed using the following equation:

$$y_{i,j} = x_{i,j} + (\Delta x'_{i,j} - \Delta x_{i,j}) \quad (4.13)$$

In the new filtering scheme α is selected as a value between the local mean and the local maximum:

$$\alpha = \text{mean}(x) + r(\max(x) - \text{mean}(x)) \quad (4.14)$$

where r is a parameter which can be selected from 0 to 1. Therefore, the difficulty of selecting proper value of α is reduced. Furthermore, the usage of local statistics make the fuzzy network can enhance images adaptively. Through adjusting the parameter of K and α at different LP layers, we can suppress noise while not damage the important details of images.

4.2.4 Filter Adjustments Based on Pyramid SNR

An object of a large area has contents which are of low frequency [75]. Therefore, edge information is kept in each LP layer. Because of the low-pass filtering and decimation, the LP decomposition has a property that the signal variation decreases with the decrease of resolution [75], [76]. The signal-to-noise ratio (SNR), which is defined as the ratio of the signal mean to its variance, will then increase in the LP layers of lower resolutions. Utilizing this, the three filters applied by us are adjusted to give different level of noise suppression and edge enhancement when processing on different LP layers. In general, the filters focus largely on noise reduction in the lowest LP layer (largest resolution) since the SNR at that layer is smallest. As the LP layer level increases (resolution decreases), the filter increases its capability on edge enhancement and decreases its noise smoothing capacity because the noise variance becomes lower. On the highest LP layer (smallest resolution), which has the largest SNR, the filter is focusing on preserving (or enhancing) edge information and its noise reduction capacity is constrained to a small level. Two common measures are taken by us to implement such SNR based filter adjustments: 1) Reduce the moving window size used by the filters as the level of LP layers increases.

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This is based on a common observation that the large moving window size is strong on noise reduction, but always causes severe damage on edges. 2) Adjust the parameters of the filters applied on LP layers to fit for the SNR level of the LP layers'. The details of adjustment on the three filters are described below.

When the LUM filter is used for our LP filtering method, we choose values of l and k near to $(N + 1)/2$ for a large amount of smoothing and a small level of edge enhancement at the lowest LP layer. In the middle LP layers l and k are set to some intermediate numbers for noise reduction and edge enhancement at some degrees simultaneously. We decrease their values as the pyramid level increases for more edge enhancement since the SNR of the layer is increasing. At the highest LP layer, l and k are both set to small values making the LUM filter focus on sharpening edges and limit noise reduction at a small level.

By changing the dimensions of the moving window and the iteration numbers of the WMMR-MED filter, we can implement the different smoothing and sharpening levels when different LP layers are processed. As the lowest LP layer contains large amount of noise, two dimensional filter window and several iterations of the filtering are applied. It is recommended to use one dimensional WMMR filter for better edge enhancement [88]. Therefore, to smooth noise and enhance edges at other LP layers, we set the filter window of the WMMR-MED as to one dimensional and apply several filtering iterations. The iteration number is increasing for more noise reduction and more edge preservation results as the LP level increases.

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When the modified fuzzy networks are applied for pyramid filtering, we adopt smoothing fuzzy network with a relative large value of α at the lowest LP layer for large amount noise reduction. At other LP layers, both the sharpening and smoothing fuzzy networks are integrated in the filter. As the level of LP layer rises, we decrease the value of α in the smoothing network to reduce the noise removal extent, and increase the value of amplifying coefficient K in the sharpening network to increase the edge enhancing capacity.

4.3 Constructing the Proposed Speckle Filter

In this section, the structure of the proposed multiscale filtering scheme to suppress speckle in ultrasound imaging is presented. The flow chart of the filtering scheme is shown and the filters to do image decomposition are analyzed.

4.3.1 Filter Structure

The LUM filter, the WMMR-MED filter, and the modified fuzzy networks are designed for additive noise suppressing. However, speckle is always considered as kind of multiplicative noise since its mean is proportional to variance. Therefore, we can not apply such filters on speckle image directly. As the LP decomposition does not change the multiplicative property of speckle, it is not recommended to use these filters processing LP layers for speckle reduction. A logarithmic transformation can be used to solve this problem. The input speckle image is first log-transformed to change the multiplicative speckle to the additive noise. The transformed image is then decomposed into four LP layers. Each LP layer is then processed by the selected filters for noise

reduction and edge enhancement. The output image is reconstructed from the filtered LP layers. Fig. 4-5 illustrates the structure of the proposed filter.

Fig.4- 5 Illustration of the structure of the proposed LP filtering

4.3.2 Resolution Reduction and Expansion Filters for LP Decomposition

When generating LP layers, 2-D low-pass filters are used before resolution reduction and expansion to avoid possible aliasing. Such a filter can be implemented by filtering images with a 1-D low-pass filter first on rows and then on columns. The following nine-tap 1-D low-pass filters are employed in the subsequent simulations to generate the LP layers of different resolutions:

$$H_e(Z) = 2H_r(Z) = 0.273 + 0.219(Z^1 + Z^{-1}) + 0.109(Z^2 + Z^{-2}) + 0.031(Z^3 + Z^{-3}) + 0.004(Z^4 + Z^{-4}) \quad (4.15)$$

Where $H_r(Z)$ and $H_e(Z)$ are the resolution reduction and expansion filters, separately. The two filters have the same frequency response, which is shown in Fig.4-6, in which we can see the cut-off frequency (-6dB) of the filter is around 0.26 (normalized). It is enough to avoid the possible aliasing.

Fig.4- 6 Frequency response of the selected filter for LP generation

4.4 Simulations and Results Analysis

In this section, the proposed pyramid filtering applying the three filters (referred as the LP-LUM, the LP-WMMR-MED and the LP-FuzzyNet) are tested using synthetic images, real phantom images, and *in vivo* data. The test results are compared with the enhanced Lee (en-Lee) filter and the method developed by Sattar, et al [14] using the ratio-of-averages (ROA) as the edge detector (referred as the Sattar-ROA filter), in terms of speckle reduction and details preservations. The Sattar-ROA filter is implemented based on LP decompositions. In the following tests, four level LP layers were used. The controlling parameter settings of each filter are described in the simulations.

4.4.1 Simulations on Synthetic Images

Synthetic images have been used by some researchers to evaluate the filters' performance. They are generated by computers in those cases that the real signals are difficult to obtain. Here we applied the method introduced by Yu, et al., [93] to form a synthetic ultrasound image.

4.4.1.1 Synthetic Image Generations

A set of RF (radio frequency) data is generated by convoluting the two-dimensional point spread function of a hypothetical ultrasound imaging system with an array representing acoustic impedance inhomogeneities. The envelope of the RF data was then detected to form the synthetic image. Following equations are used to generate the synthetic ultrasound RF data:

$$\begin{aligned}
 V(x, y) &= h(x, y) \otimes T(x, y) \\
 h(x, y) &= h_1(x)h_2(y) \\
 h_1(x) &= \sin(k_0 x) \exp[-x^2 / (2\sigma_x^2)] \\
 h_2(y) &= \exp[-y^2 / (2\sigma_y^2)] \\
 T(x, y) &= t(x, y) \cdot G(x, y)
 \end{aligned} \tag{4.16}$$

Where, $V(x, y)$ represents the ultrasonic echo RF data set. $h(x, y)$ is the two-dimensional point spread function and can be separated into the two components in axial ($h_1(x)$) and lateral ($h_2(y)$) direction, separately. $t(x, y)$ is the echogenicity model (or ultrasound cross section distribution) of the synthetic image. $G(x, y)$ is a Gaussian white noise field with zero mean and some variance. $\otimes$ represents the spatial convolution. Below are parameters applied by us when generating the test synthetic image: the center frequency

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f_0 of $h_1(x)$, which is Gaussian-weighted sinusoidal function, is set to as 5MHz. The pulse-width of transmitting ultrasonic wave σ_x is set to 1.2 and the lateral beam-width σ_y is set to 1.5. The variance of the Gaussian white noise $G(x,y)$ is 1.0. The echogenicity model $t(x,y)$ we used in tests is shown in the Fig. 4-7(a). It contains a ventricular cavity, an artery interior, a vascular wall, a rectangular target, a bright circular target, a dark circular target, two elliptical targets, three small cysts, and four point targets. The mean values of the ultrasound cross section of these targets are set as 2, 2.5, 20, 25, 18, 3.5, 3.5, 3, 1.5, and 40, respectively. The background value is set to 10.

4.4.1.2 Filter Settings in Synthetic Image Simulations

Following settings were applied in synthetic image tests to implement the SNR referred pyramid filtering. For the pyramid filtering using the LUM filter, the filter windows were set to 7x7, 5x5, 3x3, and 3x3 from the lowest LP to the highest LP; The value sets for smoother k and sharpener l were set to (22, 24), (10, 12), (2, 3), (2, 2), separately. In the proposed LP-WMMR-MED filter, the filter window in the lowest LP was set as two dimensional with the size of 7x7 and the iteration number is 3. In other LP layers, the filter windows are one dimensional. Their sizes are 5, 3, and 3 from the second layer to the fourth layer. The filtering iterations are set to 2, 3, and 3, separately. When using the proposed LP-FuzzyNet filter, only the smoothing fuzzy network was applied at the lowest LP layer for noise reduction. The filter window size is selected as 7x9 and the parameter r is selected as 0.8 in calculating α . The amplifying coefficient K is set to one. At other LP layers, both smoothing and sharpening fuzzy network were applied. From the second to the fourth LP layer, the windows used for smoothing are 5x7, 3x5, 3x3, separately. The

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window sizes for the sharpening are 5x5, 3x5, and 3x3. The ratio parameter r is 0.7, 0.5, and 0.3. And the amplifying coefficient K of each sharpening fuzzy network was selected as 4, 8, and 5.

4.4.1.3 Evaluation Parameters

Four measurements are used to evaluate the filters' performance quantitatively. The first is Mean Square Error (MSE). The MSE represents the similarity between the original image and the filtered image. The MSE can be calculated using the following equation [6]:

$$MSE = \frac{1}{N} \sum (I - \hat{I})^2 \quad (4.17)$$

Where, I represents the original image without noise, $\hat{I}$ denotes the processed image, N is the number of points in the image. The MSE can indicate the ability of global speckle suppression and detail preservations of a speckle filter. For a good speckle reduction method, it should result a small MSE.

The second measurement used is the structure similarity (SSIM) [22] to evaluate the structure preservation ability of the filter:

$$SSIM = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (4.18)$$

where μ_x and μ_y are the mean of a local window in the input and output images, respectively. σ_x and σ_y are the standard deviations of the local window in the input and output images, respectively. And C_1 , C_2 are two constants to avoid instability. Referring

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to the values suggested in [22], values of the involved parameters are decided. Images processed by filters with good feature preservation ability will have SSIM values closer to one.

The third and fourth measurement is the CNR and SSNR, which quantifies the ability of perceiving an object against a background of speckle and the ability of suppressing the background speckle, separately. The CNR and SSNR can be calculated using the equation of (3.15). They should be large values when computed in the images processed by a speckle filter.

4.4.1.3 Results and Analysis

The synthetic ultrasound image obtained by using equations in (4.19) is shown in the fig. 4-7(b). Fig. 4-7(c)~(g) show the smoothed results by the En-Lee filter, the Sattar-ROA filter, our proposed pyramid filtering methods using the LUM filter, the WMMR-MED filter and the modified fuzzy networks. The filter window size used by the En-Lee filter is set to 7×7 . Heavy blur occurred when we use larger window sizes. When applying the Sattar-ROA filter, the filter window is 3×3 to get the best edge preservations and the edge threshold is set to 1.15.

In Fig. 4-7, we can see all filters suppress speckle inside images. Among all filtered images, the proposed LP filtering with the WMMR-MED filter smooth speckle inside objects most. The LP filtering with the modified fuzzy networks suppressed more speckle in the image background. In Fig.4-7(d) which is smoothed by the Sattar-ROA filter, some

Fig.4- 7 (a) Original echogenicity model of the imaging area, (b) simulated ultrasound image with speckle. Speckle smoothing results after (c) the En-Lee filter, (d) the Sattar-ROA filter, and our proposed filters of (e) the LP-LUM filter (f) the LP-WMMR-MED filter, (g) the LP- LP-FuzzyNet filter

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	MSE	SSIM
Original image	261.9	0.39
The En-Lee	159.5	0.62
The Sattar-ROA	154.4	0.53
The LP-LUM	149.6	0.67
The LP-WMMR-MED	170.3	0.66
The LP-FuzzyNet	136.4	0.72

Table 4- 1 MSE and SSIM values calculated from the synthetic and smoothed images

	CNR					
	ROI. I	ROI. II	ROI. III	ROI. IV	ROI. V	ROI. VI
Original image	1.43	1.26	0.64	0.96	1.03	1.32
The En-Lee	2.46	1.97	1.11	1.95	1.98	2.08
The Sattar-ROA	1.84	1.46	0.72	1.40	1.17	1.53
The LP-LUM	2.83	2.27	1.29	2.12	2.17	2.59
The LP-WMMR-MED	2.85	2.44	1.29	1.82	2.39	2.80
The LP-FuzzyNet	2.38	1.96	1.28	2.01	1.96	2.22

Table 4- 2 CNR values in six areas calculated from the synthetic and smoothed images

	SSNR-1	SSNR-2
Original Image	2.05	2.05
The En-Lee	4.05	4.49
The Sattar-ROA	2.20	2.15
The LP-LUM	4.96	5.19
The LP-WMMR-MED	4.65	5.07
The LP-FuzzyNet	5.48	5.73

Table 4- 3 SSNR values calculated in the two areas in the synthetic and smoothed images

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object boundaries are lost. This is because the information at a pixel is thrown away directly if the corresponding binary mask is zero. Such information loss degrades the performance of the Sattar-ROA filter. Compared with the image filtered by the Enhanced Lee (En-Lee) method, it can be observed that the background speckle is more smoothed by our filtering scheme.

Table 4-1 contains the calculation results of MSE and SSIM. In the speckle corrupted image, the MSE is 261.9 and the SSIM is 0.39. The proposed pyramid filtering with the modified fuzzy networks gives the least MSE value and the maximum SSIM value compared with other filters, which is 136.4 and 0.72, separately. It indicated the method preserves the image details best. The proposed methods using the LUM filter reduced the MSE to 149.6 and increased the SSIM to 0.67. The MSE calculated in the image from the proposed method with the WMMR-MED filter is largest among all filtered values. However, it gives better edge preservation than the enhance Lee filter and the Sattar-ROA filter, which is indicated by the parameter of SSIM. The SSIM calculated in the Sattar-ROA filtered image is the smallest among all smoothed images. It has the least ability of preserving edges because of the information delete occurred in the filtering.

The CNR values around the six regions of interest (ROI) (labeled in Fig. 4-7(a)) in each filtered image are computed. Table 4-2 summarizes the computation results. The SSNR are computed in the areas beside the ROI I and ROI V. They are listed in the Table 4-3. The CNR and SSNR results show that the proposed pyramid filtering is capable of removing speckle while not degrading the contrast. Compared with other filtering methods, the LP-LUM filter and the LP-AWWR-MED have the best speckle reduction performance due to the relative larger CNR and SSNR values. The Sattar-

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ROA has the least SNR result because of the large extent detail loss. Considering the three quantitative evaluating parameters, MSE, SSIM, CNR and SSNR comprehensively, the proposed LP filtering combining edge enhancement and noise reduction can reduce speckle without distorting useful information and damaging the important edges.

4.4.2 Tests on Phantom Data

A real ultrasound image was obtained by scanning a phantom (403GS LE, Gammex RMI, USA) with a commercial ultrasound machine (EUB-6000, Hitachi Medical Corp., Japan). During the data acquisition, the base-band complex echo signals were recorded with the inphase and quadrature (I/Q) components. The ultrasound image is taken as the amplitude of the complex echo signals. The parameters of the proposed LP filters were set as follows to fit for the property of the real ultrasound phantom data. The filter window sizes were selected as 9x9, 7x7, 5x5, and 3x3 when applying the LP-LUM filter from the lowest LP layer to the highest LP layer. And the corresponding values of k and l for the smoother and sharpener are set as (37, 39), (20, 21), (5, 7) and (2, 3). In the LP filtering using the AWR-MED filter, the filter window sizes and dimensions are set as the same with those used in the synthetic tests. But the filtering iteration numbers at the intermediate LP layers are changed to 1, 2, and 2. The control parameters of the fuzzy network for the LP filtering are set as the same with those used in the synthetic tests.

Fig.4-8(a) gives the original real ultrasound phantom image constructed from the recorded I/Q data. Fig. 4-8(b)-(c) are smoothed results using the En-Lee filter and the

Fig.4- 8 (a) A real ultrasound phantom image and its smoothed results by (b) the En-Lee filter, (c) the Sattar-ROA filter, (d) the LP-LUM filter, (e) the LP-WMMR-MED filter, and (f) the LP-FuzzyNet filter

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Sattar-ROA filter, separately. The filtered images by our proposed LP filtering methods are shown in Fig. 4-8(d)-(f), using the LUM filter, the AWWR-MED filter, and the modified fuzzy network, separately. We can see the negative effect in the Fig. 4-8(c), which is a result of deleting information directly applied by the Sattar-ROA filter. Speckle suppression can be observed in the images processed by the proposed LP filtering methods, without destroying the important features of the circular targets. Among all smoothed images, the proposed LP-LUM filter gives the best visual evaluation results.

As there is no reference image to calculate the evaluation parameters: MSE and SSIM. We use the CNR and SSNR to measure the performance of a filter. The CNRs are calculated in each filtered image around four circular contrast regions (ROI. I-IV from left to right in the images): a high scatterer relative to the background, a gray scale target of +6 dB, a gray scale target of -6 dB, and an anechoic cyst. Table 4-4 collects the CNR obtained in images in the Fig. 4-8. The SSNRs are computed in the two areas marked in Fig. 4-8(a), which are shown in the Table 4-5.

	CNR			
	ROI. I	ROI. II	ROI. III	ROI. IV
Original image	1.69	0.49	1.37	2.49
The En-Lee	3.68	1.16	3.26	2.82
The Sattar-ROA	3.46	0.66	2.78	3.26
The LP-LUM	3.94	1.32	4.41	3.79
The LP-WMMR-MED	3.56	0.98	3.69	3.63
The LP-FuzzyNet	3.89	1.12	3.42	3.20

Table 4- 4 CNR values calculated around four circular contrast regions in the original real phantom image and the smoothed results

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	SSNR-1	SSNR-2
Original image	6.82	4.84
The En-Lee	17.87	9.16
The Sattar-ROA	5.44	7.80
The LP-LUM	27.32	11.35
The LP-WMMR-MED	19.46	9.34
The LP-FuzzyNet	29.31	15.81

Table 4- 5 SSNR values calculated in the two areas in the phantom and smoothed images

The proposed methods have a good ability on speckle suppression, which can be proven by the large values of CNRs and SSNRs shown in Table 4-4 and Table 4-5. The LP-LUM method shows the best ability on enhancing the phantom images as it leads to the largest CNRs and the second largest SSNRs. The proposed LP filtering using the fuzzy network (LP-FuzzyNet) gives larger CNR values than the En-Lee filter does in three computed regions. In the region II, the two filters have the similar performance on speckle reduction. However, the largest SSNR values obtained by the LP-FuzzyNet method proves its better performance on suppressing speckle and saving image details at the same time. The LP-WMMR-MED filter has better CNR values in the two right circular regions while it get less CNRs in the two left regions of interest, compared with the En-Lee filter. But it has larger SSNR values than the En-Lee filter. Among all filters, The Sattar-ROA filter has the least CNR and SSNR values in most areas as it deletes information in LP layers.

4.4.3 Tests on in vivo Data

A real ultrasound image of a human liver is shown in Fig. 4-9(a). The I/Q data is recorded from the ultrasound machine and the image is formed by taking the amplitude of I/Q data.

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The image is then filtered by the comparison filters and proposed filters, separately. The parameters for the proposed LP filtering using the LUM filter and the WMMR-MED are the same as those used in the real ultrasound phantom tests. The filter window sizes for the LP-FuzzyNet filter from the lowest LP layer to the highest layer are set as 7x9, 5x7, 5x5, and 3x3, while other parameters to control the fuzzy network are kept the same as those used in previous tests.

Fig. 4-9(b)-(f) shows the noise reduced images filtered by the proposed methods and selected filters. Visual observations show that the proposed LP filtering methods are capable of removing speckle and preserving significant features. The Sattar-ROA damages some edge information of the object. The En-Lee filter shows less speckle removal than the proposed method in objects and background of the real image. To evaluate the filters' performances on the real tissue images quantitatively, CNR and SSNR were calculated in selected areas in each processed image. They are listed in the Table 4-6. Indicated by the larger CNR and SSNR values, our speckle reduction method based on LP filtering combining noise reduction and edge enhancement have better performance than other comparison filters on speckle removal when processing real medical ultrasound images.

Through simulations carried out on the synthetic images, the phantom images and *in vivo* data, we can see the proposed pyramid filtering scheme has efficiency on reducing speckle while not losing any important image features.

Fig.4- 9 (a) A real ultrasound image of a human liver constructed using the *in vivo* data, and its smoothed results by (b) the En-Lee filter, (c) the Sattar-ROA filter, (d) the LP-LUM filter, (e) the LP-WMMR-MED filter, and (f) the LP-FuzzyNet filter

	CNR	SSNR-1	SSNR-2
Original image	0.58	1.11	1.48
The En-Lee	0.86	1.67	2.73
The Sattar-ROA	0.71	1.20	1.61
The LP-LUM	1.10	2.27	3.64
The LP-WMMR-MED	1.19	1.99	2.86
The LP-FuzzyNet	1.04	1.86	3.14

Table 4- 6 CNR and SSNR values calculated a real ultrasound image of a human liver and the filtered images

4.5 Conclusions and Discussions

In this chapter, a new speckle suppressing method for ultrasound imaging was discussed. The new method integrates the nonlinear edge enhancer and noise smoother to processing sub-images, which are obtained through the LP decomposition. Three filters were applied to implement the noise reduction and edge sharpening task when filtering the LP components: the LUM filter, the WMMR filter with median output, the modified fuzzy network with smoothing network and sharpening network. As each LP layer has different level of SNR, the window sizes and parameters of the applied filters were adjusted to give the increased performance, when different LP layers are processed. For example, the large filter size was used at the lower LP layers so that the filter would pay more effort on noise reduction, while small filter size was applied at higher LP layers to preserve more edges. Experiments were conducted on synthetic images, phantom images and *in vivo* data. Both visual and quantitative measurements proved the capability of the new methods on speckle reduction and feature preservation. To further evaluate the performance of the new methods, we compared the test results with those obtained from

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the En-Lee filter and the Sattar-ROA filter. Visual and quantitative comparisons showed that the proposed method reduces more speckle in homogeneous areas and kept the details more efficiently. As most ultrasound scanners contains log-compression to reduce the signal dynamic range before display, the homomorphic transformation (the log and its inverse transformation) applied in the proposed pyramid filtering scheme can be removed if the filtering is done on the images outputted by the log-compression.

Chapter 5

Adaptive Pyramid Filtering for Speckle Removal in Log-Compressed Medical Ultrasound Images

5.1 Introduction

Filtering has been studied by many researchers for smoothing speckle noise. A good filter should succeed to balance between speckle suppression and feature preservation. As most speckle filters which process on a single scale of the image, they could not reach satisfying result because in one image scale it is difficult to discriminate signals from the speckle noise [100]. Speckle filters developed in the wavelet domain are a kind of filter which can suppress speckle by processing several scales of the input image [98]-[109]. There also researchers used the pyramid for multiscale filtering to achieve good speckle removal performance [76]-[78]. When filtering speckle, one can employ a filter used for general noise reduction without considering speckle as a special kind of noise which has complex statistics, e.g. median filter [113]-[115], anisotropic diffusion [94], and soft threshold in the wavelet domain [99]. On the other hand, there are a large amount of adaptive speckle suppression filters in which the complex speckle statistics is utilized [51]-[59], [93], [100]-[104]. In these methods, a local statistical parameter was computed

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using image pixels to indicate the ‘similarity’ degree of the local speckle formation to the fully developed speckle. The filtering was then controlled by such similarities.

Medical ultrasound imaging systems often employ the logarithmic transformation to reduce the dynamic range of the input echo envelope signals to match the smaller dynamic range of the display device. Therefore, speckle filters requiring signals be processed before logarithmic compression may not be feasible any more because such signals are not usually possible in most commercial ultrasound systems. Fortunately, speckle statistic model in the log-compressed images has been studied by some researchers [5], [14] and a few filters have been developed which can suppress speckle in log-compressed images [52], [55], [94], [66].

In the previous chapter, a pyramid filtering scheme for suppressing ultrasound speckle have been discussed without considering speckle statistics. In this chapter, we will introduce an adaptive speckle filter based on the statistics of the speckle in the log-compressed images. The filter is also a multi scale filter in which the Laplacian Pyramids (LP) was applied to get multi resolution representations of the input image. The local variance at each LP layer is estimated using pixels inside the moving window. From the local variance of a LP layer and the transform functions of the filters involved to generate that layer, the signal variance before decomposition can be derived. It is then used to calculate the controlling parameter of the adaptive filter working on the LP. Therefore, the filter’s performance is controlled by the local statistics of each LP, achieving a balance between the maximum filtering by outputting the average value of the filter window, and the maximum feature saving by outputting the original value. After all LP

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layers are filtered, speckle removal can be observed in the reconstructed image without losing important object features.

This chapter consists of the following contents. The logarithmic compression model applied in medical ultrasound scanners is first introduced. Based on this model, the Dutt filter for log-compressed ultrasound images is discussed. The filter's performance is controlled by a so called 'normalized variance' representing the local speckle formation extent. The proposed pyramid speckle filtering scheme, which computes the controlling parameter based on the Dutt's study and the filtering theories, is described. To verify the filter's ability on enhancing ultrasound images, the proposed filtering scheme is tested using the synthetic data, the real ultrasound data of a phantom and *in vivo* data. At the end of the chapter, the conclusions are presented.

5.2 Adaptive Dutt Filter for Log-Compressed Signals

5.2.1 Envelope Compression in Medical Ultrasound

The dynamic range of the echo signals received by the ultrasound transducer is often larger than 60 dB. Whereas the dynamic range of a display device is often less than 50dB, e.g. the dynamic range of an 8 bit display is around 48dB ($2^8=256$, the gray level often used in common displays). Hence, medical ultrasound scanners often employ nonlinear operations to reduce the dynamic range of the echo signals to match that of the display devices. Such a dynamic range reduction is typically achieved through the logarithmic

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processing. Another advantage of applying the logarithmic compression is that it increases the contrast of objects with weak echo amplitudes.

In general, the logarithmic transfer function can be written as:

$$I(x, y) = D \ln(A(x, y)) + G \quad (5.1)$$

where, $A(x, y)$ represents a image with large dynamic range, which is formed by the echo envelope signals. D is the compression parameter and G is the linear gain of the compression. $I(x, y)$ is the image for display purpose, which has a smaller dynamic range.

5.2.2 The Dutt Speckle Filter for Log-compressed Signals

Speckle statistic model can be described using the K distribution and the Rayleigh distribution [5], [10], [11]. From the K distribution, Dutt derived the mean and variance of the ultrasound echo envelop signals [5]. Considering the logarithmic compression model of (5.1), he then derived the same two parameters for the log-compressed signals [5], [55]. Indicated by the results, the variance of the log-compressed envelope signals is a function of the scatterer density in the scanning resolution cells and the compression parameter D . Dutt then defined the normalized variance $\sigma_{norm}^2(x, y)$ respecting to the compression parameter D :

$$\sigma_{norm}^2(x, y) = \frac{24}{\pi^2} \frac{\sigma_I^2(x, y)}{D^2} \quad (5.2)$$

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where, $\sigma_I^2(x, y)$ is the variance of the log-compressed signals. The normalized variance $\sigma_{norm}^2(x, y)$ is then a function of the scatterer density only. It has a large value for small scatterer densities and reaches the unity for large scatterer densities. As the scatterer density primarily decides the speckle formations - large scatterer densities result in the fully developed speckle and small scatterer densities generate the partially developed speckle [10] [11] - the normalized variance $\sigma_{norm}^2(x, y)$ can then be used to indicate the ‘similarity’ degree of the local speckle to the fully developed speckle. Applying the normalized variance $\sigma_{norm}^2(x, y)$ as the controlling parameter in the unsharp masking filter, Dutt developed his speckle filter for log-compressed ultrasound images, which has the following format:

$$\begin{aligned}\hat{R}(x_0, y_0) &= \bar{I}(x_0, y_0) + p(x_0, y_0) \cdot (I(x_0, y_0) - \bar{I}(x_0, y_0)) \\ p(x_0, y_0) &= 1 - \frac{1}{\sigma_{norm}^2(x_0, y_0)} = 1 - \frac{\pi^2}{24} \frac{D^2}{\sigma_I^2(x_0, y_0)}\end{aligned}\quad (5.3)$$

Here, $\hat{R}(x_0, y_0)$ represents the pixel in the speckle smoothed image with the coordinate of (x_0, y_0) . $I(x_0, y_0)$ is the pixel of the log-compressed speckle image and $\bar{I}(x_0, y_0)$ is the local mean around that pixel. $p(x_0, y_0)$ is the controlling parameter computed from $\sigma_{norm}^2(x, y)$. Its range is limited to $[0, 1]$. Any larger values of $p(x_0, y_0)$ are truncated to 1. $\sigma_I^2(x_0, y_0)$ represents the variance around the image pixel $I(x_0, y_0)$.

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The local normalized variance $\sigma_{norm}^2(x_0, y_0)$ plays an important role in adjusting the filter's performance: when $\sigma_{norm}^2(x_0, y_0)$ is close to 1, it means local speckle is fully developed (because of the large scatterer density). In this condition, the value of the parameter $p(x_0, y_0)$ approaches zero and the filter performs the maximum noise reduction by outputting the local mean. If $\sigma_{norm}^2(x_0, y_0)$ is much larger than 1, 20 for example, it means scatterer density in the filtering area is very small. Point targets or edges are possibly contained in the area, which should be preserved. In this case, $p(x_0, y_0)$ is approximately zero and the filter performs no smoothing by outputting the original pixel value of the input image. In the condition that $\sigma_{norm}^2(x_0, y_0)$ is an intermediate value, 3 for example, which means speckle is partially developed, the filter balances its performance between the noise reduction and feature preservation. In the remaining contents of this chapter, the Dutt filter for log-compressed ultrasound images is referred as the Dutt-log filter.

5.3 Proposed Adaptive Pyramid Speckle Filtering

5.3.1 Pyramid Speckle Filtering Scheme

To achieve the multiscale filtering for better speckle reduction results, we performed the filtering on LP layers. The input image after the logarithmic compression is first decomposed into multiple LP layers. As the LP decomposition can be considered as passing a series of band-pass filters, each LP layer contains different frequency

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components of speckle. The new approach is to get speckle suppressed by removing the noisy component at each LP layer according to their local statistical properties.

Although there are many adaptive filters developed to smooth speckle images, most of them can not fit for our pyramid speckle filtering on the log-compressed images. First, these filters are based on the multiplicative noise model, i.e. estimating the local speckle statistics using the ultrasound echo envelope signals without log-compression. They are no longer proper to filter the logarithmic transformed images because the logarithmic operation changes the speckle statistics. Second, most speckle filters apply the mean of the signal as a component in their controlling parameter. However, such mean is removed by the subtract operation in LP generations. The local statistics filtering adopted by these filters is then no longer possible [76].

To solve the second problem, Aiazzi et al [76] proposed a so called ratio LP (RLP) filtering structure to smooth the images in synthetic aperture radar (SAR) images. In it the pyramid representations were obtained by performing the ratio operations between the adjacent Gaussian Pyramids (GP), instead of subtraction. By this means, the signal mean is preserved, allowing the Kuan multiplicative filter to be used for smoothing the RLP layers. Since speckle is always considered as a kind of multiplicative noise and the logarithmic operation changes the multiplication into the addition, one can apply additive noise filters to smooth the log-compressed speckle images, e.g. the pyramid filtering method with the Kuan additive noise filter also reported by Aiazzi et al [77]. However, the filter has two limitations. First, it does not give accurate estimations of speckle formation extent in LP layers. This will degrade the filter's ability on speckle removal.

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Second, it requires selecting the reference noise variance in advance. The selection mainly depends on operator's experience.

In my new pyramid speckle filtering scheme, the Dutt-log structure is applied to smooth the LP layers. The filter's controlling parameter is computed considering both the statistical model of the log-compressed echo envelope signals and the procedures of the LP generations. Therefore, the proposed filter's performance is adjusted by the local speckle formations, which can avoid damaging important image features. Furthermore, the controlling parameter of the filter does not require calculating the signal mean, which is removed by subtraction operation in LP representation generations. This made it applicable to filter LP representations. Fig. 5-1 illustrates our pyramid speckle filtering scheme for log-compressed ultrasound images.

Fig. 5- 1 Illustration of adaptive pyramid speckle filtering scheme for log-compressed medical ultrasound images

5.3.2 Estimations of Speckle Formation Similarity in LP Layers

The Dutt-log filter structure is applied as the smoother working on each LP layer. The filter will remove noise and preserve detail information according to the local speckle formations, which can be estimated by the signal variance [56]. However, as a LP layer is a band-pass representation of the input image, it contains speckle information only within a specific frequency band. The variance computed at a LP layer can not be used to indicate the speckle formation extent of the processing area in the input image. Respecting to the operations involved in generating a specific LP layer, we derived the virtual variance related to the layer. The virtual variance can be considered as indicating speckle formations of the corresponding LP layer and be used to control the Dutt-log filter's performance.

The LP decomposing operations mainly consist of the subtraction and low-pass filtering. Referring to Fig. 5-1, the k^{th} LP layer (except the highest LP layer) can be obtained by subtracting the k^{th} expanded GP layer from the GP layer at the same level [72]:

$$L_k = G_k - \tilde{G}_k \quad (5.4)$$

where L_k ($k > 0$) represents the k^{th} LP layer, G_k is the GP at k^{th} layer (the input image is represented by G_0). $\tilde{G}_k$ denotes the expanded GP layer from G_k .

Hence, the variances of a LP layer and its generating GP layers have the following relationship [76]:

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$$\sigma_L^2(k) = \sigma_G^2(k) + \sigma_{\tilde{G}}^2(k) - 2\text{cov}(G_k, \tilde{G}_k) \quad (5.5)$$

where, $\sigma_L^2(k)$ is the variance of L_k , $\sigma_G^2(k)$ and $\sigma_{\tilde{G}}^2(k)$ are the variances of G_k and $\tilde{G}_k$, separately. $\text{cov}(G_k, \tilde{G}_k)$ denotes the covariance coefficient between G_k and $\tilde{G}_k$.

The GP and expanded GP layers can be considered as passing the input image through a series of low pass filters [72], [73]:

$$\begin{aligned} G_0 &= I(m, n) \\ G_k &= (\downarrow 2)[h_r(n_1, n_2) \otimes G_{k-1}] \\ \tilde{G}_k &= h_e(n_1, n_2) \otimes (\uparrow 2)[G_k] \end{aligned} \quad (5.6)$$

where, $I(m, n)$ is the input image. In the new pyramid filtering scheme, it is a log-compressed speckle image. $h_r(n_1, n_2)$ and $h_e(n_1, n_2)$ are the two-dimensional (2-D) low-pass filters for resolution reduction and expansion, separately. $(\downarrow 2)[.]$ denotes decimating by 2 and $(\uparrow 2)[.]$ represents interpolating by 2. $\otimes$ means linear convolution. The two dimensional (2-D) low pass filter can be implemented by filtering image rows and columns subsequently with a one dimensional (1-D) filters. Here we use $h_r(n)$ and $h_e(n)$, $(n = -M, \dots, M)$ to represent the 1-D low pass filter kernels employed for implementing $h_r(n_1, n_2)$ and $h_e(n_1, n_2)$, separately. Their frequency responses are denoted by $H_r(\omega)$ and $H_e(\omega)$, separately. If $H_r(\omega)$ and $H_e(\omega)$ are negligible outside their passbands, i.e. aliasing is very small, $\sigma_G^2(k)$, $\sigma_{\tilde{G}}^2(k)$ and $\text{cov}(G_k, \tilde{G}_k)$ can be calculated as the following [73], [77]:

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$$\begin{aligned}
\sigma_G^2(k) &= \sigma_I^2(k) \cdot \left(\frac{1}{2\pi} \int_{-\pi}^{\pi} |H_k^{eq}(\omega)|^2 d\omega \right)^2 = \sigma_I^2(k) \cdot (\rho_k^G)^2 \\
\sigma_{\tilde{G}}^2(k) &= \sigma_I^2(k) \cdot \left(\frac{1}{2\pi} \int_{-\pi}^{\pi} |\tilde{H}_k^{eq}(\omega)|^2 d\omega \right)^2 = \sigma_I^2(k) \cdot (\rho_k^{\tilde{G}})^2 \\
\text{cov}(G_k - \tilde{G}_k) &= \sigma_I^2(k) \cdot \left(\frac{1}{2\pi} \int_{-\pi}^{\pi} |H_k^{eq}(\omega)| \cdot |\tilde{H}_k^{eq}(\omega)| d\omega \right)^2 = \sigma_I^2(k) \cdot (\rho_k^{G\tilde{G}})^2
\end{aligned} \tag{5.7}$$

where, $\sigma_I^2(k)$ represents the virtual variance coefficient related to the k^{th} LP layer L_k before decomposition. $H_k^{eq}(\omega)$ and $\tilde{H}_k^{eq}(\omega)$ are the frequency responses of the equivalent filters used to generate G_k and $\tilde{G}_k$, separately. They can be derived from the filter series used in generating the k^{th} LP layer. ρ_k^G and $\rho_k^{\tilde{G}}$ are the power gain of the equivalent filter $H_k^{eq}(\omega)$ and $\tilde{H}_k^{eq}(\omega)$, separately. $\rho_k^{G\tilde{G}}$ is the cross power gain between the equivalent filter $H_k^{eq}(\omega)$ and $\tilde{H}_k^{eq}(\omega)$. Because all filtering are performed to implement 2-D operations, the power gains should be squared.

Substitute items in the equation (5.6) with the equation (5.7), we can get:

$$\sigma_L^2(k) = [(\rho_k^G)^2 + (\rho_k^{\tilde{G}})^2 + (\rho_k^{G\tilde{G}})^2] \cdot \sigma_I^2 \tag{5.8}$$

Therefore, we obtain the virtual variance $\sigma_I^2(k)$ related to L_k once we get $\sigma_L^2(k)$, the variance of L_k :

$$\sigma_I^2(k) = \frac{\sigma_L^2(k)}{(\rho_k^G)^2 + (\rho_k^{\tilde{G}})^2 + (\rho_k^{G\tilde{G}})^2} \tag{5.9}$$

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Now we consider how to calculate the power gains involved in (5.8), using the filter coefficients. The frequency response $H_k^{eq}(\omega)$ of the equivalent filter $h_k^{eq}(n)$ for generating GP layer G_k can be given by [73]:

$$H_k^{eq}(\omega) = \begin{cases} 1, & k = 0 \\ H_r(\omega)H_r(2\omega)\cdots H_r(2^k\omega), & k > 0 \end{cases} \quad (5.10)$$

where, $H_r(2^k\omega)$ is the frequency response of the up-sampled reduction filter $h_{r_k}(n)$, whose coefficients can be obtained by interleaving the coefficients of the reduction filter $h_r(n)$ with $2^k - 1$ zeros, i.e. up-sampling $h_r(n)$ by 2^k :

$$h_{r_k}(n) = (\uparrow 2^k)[h_r(n)] \quad (5.11)$$

Therefore, the coefficients of the equivalent filter $h_k^{eq}(n)$ can be calculated as the linear convolution of the reduction filter $h_r(n)$ and its up-sampled versions $h_{r_l}(n), l = 1, 2, \dots, k$:

$$h_k^{eq}(n) = \begin{cases} \delta(n) & k = 0 \\ h_{r_0}(r) \otimes h_{r_1}(r) \otimes \cdots \otimes h_{r_k}(r) & k > 0 \end{cases} \quad (5.12)$$

where, $\delta(n)$ is the impulse function, $\otimes$ denotes linear convolution.

Similarly, the frequency response $\tilde{H}_k^{eq}(\omega)$ of the equivalent filter $\tilde{h}_k^{eq}(n)$ for generating the k^{th} expanded GP layer $\tilde{G}_k$ can be given by the following equation [72]:

$$\tilde{H}_k^{eq}(\omega) = H_{k+1}^{eq}(\omega)H_e(2^k\omega) \quad (5.13)$$

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where, $H_e(2^k \omega)$ denotes the frequency response of the up-sampled expansion filter

$h_{e_k}(n)$, which is derived by up sampling the resolution expansion filter $h_e(n)$ with 2^k :

$$h_{e_k}(n) = h_e(n) \uparrow 2^k \quad (5.14)$$

The coefficients of $\tilde{h}_k^{eq}(n)$ can then be calculated by linearly convoluting the equivalent

reduction filter $h_{k+1}^{eq}(n)$ with the filter $h_{e_k}(n)$:

$$\tilde{h}_k^{eq}(n) = h_{k+1}^{eq}(n) \otimes h_{e_k}(n) \quad (5.15)$$

From the properties of the discrete Fourier Transformation, the power gains ρ_k^G , $\rho_k^{\tilde{G}}$ and

$\rho_k^{G\tilde{G}}$ can be computed using the coefficients of the relevant equivalent filters as:

$$\begin{aligned} \rho_k^G &= \frac{1}{2\pi} \int_{-\pi}^{\pi} |H_k^{eq}(\omega)|^2 d\omega = \sum_n |h_k^{eq}(n)|^2 \\ \rho_k^{\tilde{G}} &= \frac{1}{2\pi} \int_{-\pi}^{\pi} |\tilde{H}_k^{eq}(\omega)|^2 d\omega = \sum_n |\tilde{h}_k^{eq}(n)|^2 \\ \rho_k^{G\tilde{G}} &= \frac{1}{2\pi} \int_{-\pi}^{\pi} \left(|H_k^{eq}(\omega)| \cdot |\tilde{H}_k^{eq}(\omega)| \right) d\omega = \sum_n \left(|h_k^{eq}(n)| \cdot |\tilde{h}_k^{eq}(n)| \right) \end{aligned} \quad (5.16)$$

Utilizing equations (5.9) and (5.16), we can compute the virtual variance related to a LP layer from the variance of the layer and the coefficients of the equivalent filter generating the layer.

5.3.3 Adaptive Filter Structure for Pyramid Smoothing

The new pyramid filtering scheme is to smooth each LP layer adaptively with the Dutt-log filter. The controlling parameter of the Dutt-log filter for smoothing the k^{th} LP layer is computed using the equation (5.9). The smoothing filter in the k^{th} LP layer can be expressed as the following equation:

$$\begin{aligned}\hat{L}_k(x_0, y_0) &= \overline{L}_k(x_0, y_0) + p_k(x_0, y_0) \cdot (L_k(x_0, y_0) - \overline{L}_k(x_0, y_0)) \\ p_k(x_0, y_0) &= 1 - \frac{1}{\sigma_{norm}^2(x_0, y_0)} = 1 - \frac{\pi^2}{24} \frac{D^2}{\sigma_I^2(k, x_0, y_0)} \\ \sigma_I^2(k, x_0, y_0) &= \frac{\sigma_L^2(k, x_0, y_0)}{(\rho_k^G)^2 + (\rho_k^{\tilde{G}})^2 + (\rho_k^{G\tilde{G}})^2}\end{aligned}\tag{5.16}$$

where, $\hat{L}_k(x_0, y_0)$ denotes a pixel in the smoothed k^{th} LP layer L_k with the coordinate of (x_0, y_0) . $\overline{L}_k(x_0, y_0)$ represents the local mean of L_k around the pixel $L_k(x_0, y_0)$. $p_k(x_0, y_0)$ is the control parameter at the pixel for smoothing L_k . $\sigma_I^2(k, x_0, y_0)$ denotes the virtual local variance related to the LP layer L_k . $\sigma_L^2(k, x_0, y_0)$ represents the local variance of L_k . The power gains ρ_k^G , $\rho_k^{\tilde{G}}$ and $\rho_k^{G\tilde{G}}$ can be computed using the equations (5.9)~(5.15). Using the statistical estimation method, $\sigma_L^2(k, x_0, y_0)$ can be computed using the pixels inside the filter window:

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$$\begin{aligned}
\sigma_L^2(k, x_0, y_0) &= \overline{L_k^2}(x_0, y_0) - \overline{L_k}^2(x_0, y_0) \\
\overline{L_k^2}(x_0, y_0) &= \frac{1}{N} \sum_{(x,y) \in \Omega} L_k^2(x, y) \\
\overline{L_k}(x_0, y_0) &= \frac{1}{N} \sum_{(x,y) \in \Omega} L_k(x, y)
\end{aligned} \tag{5.17}$$

where, $\overline{L_k^2}(x_0, y_0)$ represents the local square mean around the (x_0, y_0) at L_k . $L_k(x, y)$ denotes a pixel inside the filter window. Ω is the pixel set of the filter window, whose center is at $L_k(x_0, y_0)$. N is the size of Ω , i.e. the number of pixels inside the filter window.

5.4 Simulation Results

In this section, the experiment results of the proposed adaptive LP filtering for speckle removal in log-compressed ultrasound images are presented. The experiments were carried out using the synthetic ultrasound echo data, the real ultrasound echo data of a phantom, and *in vivo* data of a human liver. Before filtering, each data set is first compressed with a specific compression parameter D to meet the dynamic range of the display. Three filters reported by other researchers which can be used in smoothing log-compressed medical ultrasound images were also tested as comparisons. They are referred as the AWMF [52], the Dutt-log filter [55], and the Ghofrani filter [66].

In the following tests, four level LP layers were used in our pyramid decomposition. The 1-D kernels of the resolution reduction filter $h_r(n)$ and the expansion filter $h_e(n)$ were

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both selected as half-band. Different filters have been assessed in the proposed filter. Based on the filter assessment results, we used the 1-D kernel same as the one employed by Aiazzi [76] for the reduction and expansion filters:

$$H_e(z) = 2H_r(z) = 1 + 0.61(z + z^{-1}) - 0.145(z^3 + z^{-3}) + 0.042(z^5 + z^{-5}) - 0.007(z^7 + z^{-7}) \quad (5.18)$$

where, $H_r(z)$ and $H_e(z)$ represent the Z transforms of the reduction filter $h_r(n)$ and the expansion filter $h_e(n)$. The frequency response of the filter is plotted in Fig. 5-2.

Fig. 5- 2 Frequency response of the selected 1-D filter kernel.

From Fig. 5-2, a good aliasing rejection can be found outside the pass-band of the selected filter. As only nine nonzero coefficients are contained in the selected filter, it also reduces the computation cost.

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The compression parameter D for each data set was computed from the dynamic range of the envelop data and that of the display device. In the following tests, the dynamic range of the input envelop data was estimated using its maximum and minimum values. The display resolution was supposed to be 256 gray levels (8bits).

5.4.1 Tests on the Synthetic data

Synthetic images were generated using the method reported by Yu, *et al* [93] and tested. Here the results from processing the same synthetic image data as the one used in the previous chapter are shown.

The generated synthetic RF data was recorded with the inphase and quadrature components (I/Q data), from which we got the envelope signals. According to the dynamic range of the echo envelope data, the compression parameter D was calculated as 26.17 for the 256 gray level display. When filtering the log-compressed data, the filter window of each filter to be tested was set to 7×7 . The scaling factor and the central weight of the AWMF were set to 13 and 110, separately.

Fig. 5-3(a) and (b) show the geometry of the synthetic phantom and the synthetic image constructed from the log-compressed signals. Fig. 5-3 (c)~(f) presents the smoothed results processed by the proposed pyramid filtering method, the AWMF method, the Dutt-log filter, and the Ghofrani filter. In Fig. 5-3(b) we can see image structures are blurred by the granular speckle pattern, especially in the low contrast areas. In the images

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Fig. 5- 3 Test results using the synthetic ultrasound data. (a) geometry of the synthetic phantom, (b) original log-compressed synthetic image, and smoothed by (c) the proposed method, (d) the AWMF, (e) the Dutt-log filter, and (f) the Ghofrani filter

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smoothed by the four filters, speckle were suppressed. Among the four enhanced images, the homogeneous areas in the image filtered by the proposed method were found smoother than those in other filtered results. In the images processed by the comparison filters, we can still observe noise existence due to the insufficient filtering, especially in the image processed by the Ghofrani filter. Noise also can be observed around the object boundaries in these images.

The four measurements, the mean square error (MSE), the structure similarity (SSIM), the contrast-to-noise ratio (CNR), and the speckle signal-to-noise ratio (SSNR) are calculated to evaluate the filters' performance in quantities. Their definitions can be found in Chapter 4. Table 5-1 contains the calculation results of MSE and SSIM in the synthetic ultrasound image and the filtered images shown in the Fig. 5-3. In Table 5-1, the proposed pyramid filtering scheme gives a MSE value of 307.74, which is smaller than the MSE values obtained by other filters. The proposed filtering scheme provides the largest SSIM value among all filters, which is 0.79. The Ghofrani filter got the smallest values of the SSIM (0.62), which means it has the least edge preservation ability among the four filters. The SSIMs are 0.72 in the AWMF and 0.75 in the Dutt-log filter.

The CNR values around the six regions of interest (ROI) (labeled in the Fig. 5-3(a)) in the filtered images are computed. Table 5-2 summarizes the computation results. The large CNR values obtained by the proposed pyramid filtering show that the method is capable of removing speckle while not degrading the detail contrast. Compared with other filtering methods, the proposed method has the largest CNR results in most areas. It means objects are easier to be perceived in the image smoothed by our method. This is

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	MSE	SSIM
Original image	545.56	0.26
The Proposed method	307.74	0.79
The AWMF method	406.92	0.72
The Dutt-Log filter	326.02	0.75
The Ghofrani filter	350.08	0.62

Table 5- 1 MSE and SSIM values calculated from the log-compressed synthetic image and the smoothed results

	CNR					
	ROI. I	ROI. II	ROI. III	ROI. IV	ROI. V	ROI. VI
Original image	1.46	1.11	0.67	1.01	0.89	1.19
The Proposed method	2.87	2.28	1.63	2.26	1.88	2.28
The AWMF method	2.60	2.12	1.48	2.06	1.91	2.03
The Dutt-Log filter	2.74	2.21	1.54	2.26	2.05	2.07
The Ghofrani filter	2.35	1.84	1.26	1.79	1.54	1.77

Table 5- 2 CNR values in six areas calculated from the log-compressed synthetic image and the smoothed images

	SSNR-1	SSNR-2
Original image	10.20	10.80
The Proposed method	25.21	29.95
The AWMF method	20.86	26.11
The Dutt-Log filter	23.05	29.14
The Ghofrani filter	17.38	21.23

Table 5- 3 SSNR calculated in the log-compressed synthetic image and the smoothed images

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consistent with the visual comparison results. The SSNR are also computed in the two areas in images obtained. The proposed method got the largest SSNR values and the Grofrani filter generated the least SSNRs. Considering the four quantitative evaluating parameters together, the proposed adaptive pyramid filtering method reduces speckle effectively without losing important features when processing on the synthetic images.

5.4.2 Tests on the Real Phantom Data

A set of real ultrasound data was obtained by scanning a phantom (403GS LE, Gammex RMI, USA) with a commercial ultrasound machine (EUB-6000, Hitachi Medical Corp., Japan). The base band echo signals were recorded with the inphase and quadrature (I/Q) components. The ultrasound image was then constructed from the logarithmic compressed amplitude of the echo signals.

As the display has the 256 gray level, the compression parameter D for the real ultrasound phantom data was calculated as 24.85. The filter window of each filter was set to 7×7 when working the phantom data set. The scaling factor and the central weight of the AWMF were set to 15 and 119, separately.

Fig. 5-4(a) shows the log-compressed phantom image constructed from the recorded real phantom data. The phantom contains four circular contrast regions (referred as ROI. I-IV from left to right in the images): a high scatter relative to the background, a gray scale

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target of +6 dB, a gray scale target of -6 dB, and an anechoic cyst. Fig. 5-4(b)~(e) presents the quality improved images by using the proposed adaptive pyramid filtering method, the AWMF method, the Dutt-log filter, and the Ghofrani filter, separately. In Fig. 5-4(b), efficient speckle removal can be observed in the entire image and the four targets are preserved without distortion. In other three smoothed images (Fig. 5-4(c)~(e)) there are still noise left due to insufficient filtering, especially in the images filtered by the AWMF and the Ghofrani filter.

To quantitatively evaluate the performances of the four filters' on the real ultrasound phantom data, CNR values of the four circular targets are computed in the original log-compressed image and the filtered images. Table 5-4 presents the CNR values obtained. Among the four filters, the proposed adaptive pyramid filtering gave the largest CNR values: 3.99, 1.24, 4.23, and 3.56. The Dutt-log increased the CNRs close to the proposed method, which are 3.78, 1.15, 3.56, and 3.36. The SSNR are computed in the two areas in the original log-compressed phantom image and those processed by the filters. The results are contained in the Table 5-5. The proposed method suppressed the background speckle most because it got the largest SSNR values, which are 28.96 and 13.36 separately. Through visual and quantitative comparisons using the phantom data, the proposed method shows a good ability on removing speckle and preserving image details.

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Fig. 5- 4 Test results using the real ultrasound data of a phantom. (a) original log-compressed phantom image, and smoothed by (b) the proposed adaptive pyramid filtering method, (c) the AWMF, (d) the Dutt-log filter, and (e) The Ghofrani filter

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	CNR			
	ROI. I	ROI. II	ROI. III	ROI. IV
Original image	1.69	0.49	1.36	2.49
The Proposed method	3.99	1.24	4.23	3.56
The AWMF method	3.04	0.85	2.32	2.90
The Dutt-Log filter	3.78	1.15	3.56	3.36
The Ghofrani filter	2.92	0.88	2.58	3.14

Table 5- 4 CNR values calculated around four circular contrast regions in the original real phantom image and the smoothed images

	SSNR-1	SSNR-2
Original image	7.92	5.69
The Proposed method	28.96	13.36
The AWMF method	16.93	8.16
The Dutt-Log filter	24.59	12.14
The Ghofrani filter	16.41	9.99

Table 5- 5 SSNR calculated in the log-compressed image and the smoothed images using the phantom data

5.4.3 Tests on *in vivo* Data

The same commercial ultrasound scanner (EUB-6000, Hitachi Medical Corp., Japan) was used to obtain *in vivo* data of a human liver. The I/Q components of the base-band signal were recorded to compute the amplitudes of the echoes. The amplitude signals were then compressed by the logarithmic function for display purpose. The proposed pyramid filtering and the three comparison filters were employed to remove speckle in the compressed image. In this case, the compression parameter D was computed as 24.85.

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The moving windows size of each filter was set to 7×7 . The scaling factor and the central weight of the AWMF were set to 15 and 119, separately.

Fig. 5-5(a) shows the original log-compressed liver image. The speckle smoothed images by the four filters are presented in Fig. 5-5(b)~(e). Visual observations show that the proposed adaptive pyramid filtering method is capable of removing speckle and preserving significant features. In the images processed by the AWMF and the Ghofrani filter we can observe some noise left, especially in the low gray level areas. Compared with the image smoothed by the Dutt-log filter, edges in the image filtered by the proposed method are more noticeable. Visually, noise around the edges of the objects is not sufficiently reduced in the images processed by the Dutt-log filter, the AWMF, and the Ghofrani filter.

CNR values around the center area were calculated in the original liver image and the speckle smoothed images. They are listed in the Table 4. From it, we can see the CNRs are increased from 1.37 in the original image to 1.99 by the proposed method, 1.78 by the AWMF, 1.88 by the Dutt-Log filter, and 1.76 by the Ghofrani filter. Table 5-6 presents the SSNR values which were computed in two areas in the images obtained. From the SSNRs obtained, we can see the proposed method suppresses speckle most among the four filters as its SSNR values are largest. The largest CNR and SSNR values obtained by the proposed adaptive pyramid filtering method prove its strong ability on enhancing log-compressed ultrasound images, respecting to speckle reduction and detail preservations.

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Fig. 5- 5 Test results using *in vivo* data of a human liver. (a) original log-compressed liver image, smoothed by (b) the proposed adaptive pyramid filtering method, (c) the AWMF, (d) the Dutt-log filter, and (e) The Ghofrani filter

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	CNR	SSNR-1	SSNR-2
Original image	1.37	4.81	5.09
The Proposed method	1.99	7.01	11.22
The AWMF method	1.78	6.20	7.90
The Dutt-Log filter	1.88	6.83	10.68
The Ghofrani filter	1.76	6.25	8.34

Table 5- 6 CNR and SSNR values computed in the real log-compressed ultrasound image and the filtered images using *in vivo* data

5.5 Conclusions

As the ultrasound echo signals have larger dynamic range than a display device has, the logarithmic transformation is often employed in medical ultrasound imaging systems before display an image. In this chapter, an adaptive pyramid filtering scheme for reducing speckle in such log-compressed ultrasound images was discussed. The LP representations of a log-compressed speckle image were first obtained. Because each LP layers consists of objects and noise information in a specific frequency band, an adaptive filter was then employed to smooth LP layers according to their noise level. The Dutt-log filter was selected to perform the LP filtering. It has good speckle reduction ability using local speckle statistics. Another advantage of the filter is that it does not use the signal mean to control the filter's performance, which has been canceled theoretically by subtractions in generating LP layers. The estimated virtual variance, which can represent speckle formation extent of an area at a LP layer, can be obtained using the local variance at the layer and coefficients of the equivalent filter used to generate the layer. The

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performance of the Dutt adaptive filter on that LP layer is then controlled by the virtual variance to smooth noise and save features of the layer simultaneously. The proposed method was tested using the synthetic ultrasound data, the real ultrasound data of a phantom and *in vivo* data. Its performance was also compared with some adaptive filters developed for smoothing the log-compressed ultrasound images. Both visual observations and quantitative measurements proved the capability of the new methods on speckle reduction and features preservation.

Chapter 6

Conclusions and Suggested Future Works

6.1 Conclusions

The main aim of the research work in this thesis is the development of efficient methods to suppress speckle in medical ultrasound images. To meet this target, spatial compounding and filtering techniques are studied in details. Based on our studies, a new spatial compounding and two image filtering schemes were proposed for reducing ultrasound speckle. All the methods developed should be helpful in enhancing B-mode ultrasound images.

Spatial compounding can suppress speckle through averaging multi images obtained with varied ultrasound spatial orientations. In the new developed spatial compounding, we divided subapertures both in the transmit and receive stages. A virtual transducer can be formed through combining a TSA and RSA. By activating different virtual transducers the averaging images with different spatial orientations were acquired. The new method is referred as the TRSAC. The TSA and RSA component in our subaperture combinations can

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be the same or not. Through this way, the number of images that can be used for averaging is increased from N in the subarray compounding to N^2 in our TRSAC (N is the number of subapertures divided in the transducer). When the subapertures do not contain overlapping elements among each other, images obtained by the TRSAC can be considered as ‘almost’ uncorrelated. In this condition, the TRSAC has good ability on enhancing ultrasound images by suppressing speckle efficiently. The improvement of the proposed TRSAC will decrease if we employ overlapping subapertures. Below an overlapping limit, the TRSAC works better than the subarray compounding because it generates relatively larger number images for averaging.

Both of the proposed filtering methods are developed based on the concepts of multiscale filtering. The Laplacian Pyramid was employed by them as the way to get multi-resolution representations of the input speckle image. To avoid damaging important image details, a noise smoother and an edge enhancer were integrated in the filter simultaneously which works on the LP layers. Three filters combining noise reduction and edge enhancement were applied and tested in the first LP filtering method. Unlike the first method, the second proposed filtering method smoothes speckle at each LP layer adaptively, based on the local speckle formation extents. The main processing of the second method is to compute the similarity degree of the local speckle at a LP layer to the fully developed speckle, utilizing the local variance and the coefficients of the anti-aliasing filters used for generating the layer. The computing result is then used to control the performance of the Dutt filter, which was developed for smoothing speckle in log-compressed images. The simulation results showed that the both LP filtering methods have efficiency on suppressing ultrasound speckle without damaging image features.

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Either the proposed new spatial compounding or the multiresolution filtering schemes can be integrated into the ultrasound scanner as an optional operation for the medical doctors when they want to see speckle smoothed images. The TRSAC requires additional control circuits to switch the active subapertures and implement the subaperture focusing and beamforming. It also needs more memories to store compounding images temporarily. These requirements increase the hardware cost. The multiresolution filtering schemes can be implemented in the modern digital signal processors (DSPs) as an image processing module. It requires some skills in DSP programming and time cost should be considered. The TRSAC method has the merit that it not only removes speckle, but also suppresses other kind of artifacts, such as clutters. The advantage of filtering scheme is that it can be implemented in a common computer as an application and doctors can use it to process the images they wanted in an off-line mode. This requires no modification on the scanner in hand while a special scanner needed to be ordered if the TRSAC is selected as a help.

6.2 Suggested Future Works

Following works can be carried on based on the research results obtained:

1. As the nature of the spatial compounding, it not only reduces speckle in ultrasound image, but suppresses other kind of artifacts, such as the clutter which arises from side lobes, grating lobes, multi-path reverberation and other acoustical phenomena [21]. The proposed TRSAC has been proved efficient in removing speckle. Studies can be performed on exploring the ability of the TRSAC on suppressing other artifacts like clutter. Such research needs to analyze the formation of such artifacts

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and their negative impacts on image qualities. Methods for carrying out the experiments which can evaluate the TRSAC's ability on suppressing these artifacts should be found out. It will be convictive if the comparisons can be made on the performances between the TRSAC and other spatial compounding methods.

2. The proposed LP filtering methods proved the effectiveness of the multiscale denoising on suppressing ultrasound speckle. However, the outcomes of the proposed methods are not so inspiring and further improvements can be achieved in this area. More research works can be focused on finding robust filters to smooth multi-resolution representations of the speckle image. There are also other image decomposition methods which may be better for the proposed multiscale filtering scheme. In any research work following on, people should study the speckle pattern and the filter performance in each resolution layer if they want to obtain good speckle suppression result.
3. Following with the rapid developments of the very large scale integration (VLSI) and the computer science, speckle suppression algorithms have the potential to be integrated into the commercial ultrasound scanners if they can be implemented in a programmable hardware platform, such as digital signal processors and general-purpose processors. There are a lot of works to be done when mapping an algorithm into such programmable devices, including our LP based speckle filters. People who decided to develop in this area need to get familiar with the structure and specific tools the selected processor provides. The time consumption will be a great challenge when implementing the filtering method in software. The processing

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ability should be fully utilized to meet the requirements of real-time implementation.

Pipeline, data paths, memory allocations, and instruction organizations are the main problems to be studied and tested.

Author's Publications

1. LC. Zhang, J. Cao, EMC. Wong, "Transmit-Receive Subaperture Compounding Using a Phased Array," submitted to *International Journal of Imaging Systems and Technology*
2. LC. Zhang, F. Zhang, EMC. Wong, "Multiscale Speckle Reduction Combining Edge Enhancement and Noise Removal," submitted to *EURASIP Journal on Image and Video Processing*
3. LC. Zhang, EMC. Wong, "Adaptive Pyramid Filtering for Speckle Removal in Log-Compressed Medical Ultrasound Images," to be submitted to *Ultrasonics*
4. LC. Zhang, EMC. Wong, "Adaptive Speckle Reduction Based on Nakagami distribution In Medical Ultrasound Imaging," *Proceedings of the 1st International Bioengineering Conference (IBEC)*, Aug. 2004
5. LC. Zhang, EMC. Wong, L. M. Koh, L. S. Ng, "An adaptive filter for speckle reduction in medical ultrasound image processing," *8th Control, Automation, Robotics and Vision Conference (ICARCV)*, vol. 1, pp. 654-658, Dec, 2004
6. LC. Zhang, EMC. Wong, F. Zhang, J. Zhou, "Adaptive pyramid filtering for medical ultrasound image enhancement," in *Proceedings of IEEE International Symposium on Biomedical Imaging (ISBI 2006)*, vol
7. C. Gao, LC. Zhang and E. M. C. Wong, "Design of a digital phase shift beamformer for ultrasonic imaging," in *Proceedings of IEEE International Workshop on Biomedical Circuits and Systems*, pp. S2.2: 13-16, Dec. 2004
8. F. Zhang, Y. M. Yoo, LC. Zhang, L. M. Koh, and Y. Kim, "Multiscale nonlinear diffusion and shock filter for ultrasound image enhancement," to appear in *the Proceedings. of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, New York, June, 2006

Bibliography

- [1] C. B. Burckhardt, "Speckle in Ultrasound B-mode Scans," *IEEE Transactions on Sonics and Ultrasonics*, Vol. SU-25, No.1, pp.1-6, Jan. 1978
- [2] R. F. Wagner, S. W. Smith, J. M. Sandirk, and H. Lopez, "Statistics of speckle in ultrasound B-Scans", *IEEE Transactions on Sonics and Ultrasonics*, Vol. 30, No. 3, pp.156-163, May 1983.
- [3] L. Weng , J. Reid, P. M. Shankar, and K. Soetanto, "Ultrasound Speckle Analysis Using K-distribution," *Journal of Acoustic Society American*, vol. 89, June 1991.
- [4] P. M. Shankar, "A General Statistical model for Ultrasonic Backscattering from Tissues," *IEEE Transactions on Ultrasonics, Ferroelectronics, and Frequency Control*, vol. 47, no. 3, May 2000
- [5] Vinayak Dutt, *Statistical Analysis of Ultrasound Echo Envelope*, Ph.D. dissertation, Mayo Graduate School, Rochester, MN, 1995
- [6] R. C. Molthen, V. Manoj Narayanan, P. M. Shankar, J. M. Reid, Vo Genis and L. Vergara-Dominguez, "Ultrasound echo evaluation by K-Distribution," *IEEE Ultrasonics Symposium*, pp.957-960, 1993
- [7] V. Manoj Narayanan, P.M. Shankar, and John, M. Reid, "Non-Rayleigh statistics of Ultrasonic Backscattered Signals," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 41, No. 6, pp. 845-852, Nov. 1994
- [8] P. M. Shankar, J. M. Reid, H. Ortega, C. W. Piccoli, and B. B. Goldberg, "Use of non-Rayleigh Statistics for The Identification of Tumors in Ultrasonic B-scans of the Breast," *IEEE Transactions on Medical Imaging*, vol. 12, no. 4 Dec 1993

- [9] J. G. Abbot, and F. L. Thurstone, "Acoustic Speckle: Thoery and Experimental Analysis", *Ultrasonic Imaging*, Vol. 1, pp303-324, 1979.
- [10] P. N. T. Wells and M. Halliwell, "Speckle in Ultrasonic Imaging," *Ultrasonics*, Vol. 19, pp.225-229, Sep. 1981
- [11] J. C. Bamber and R. J. Dickinson, "Ultrasonic B-scanning: a Computer Simulation," *Physics in Medicine and Biology*, Vol. 25, No.3, pp.463-479, 1980
- [12] R. W. Prager, A. H. Gee, G. M. Treece, L. H. Berman, "Decompression and Speckle Detection for Ultrasound Images using the Homodyned K-distriution," *Pattern Recognition Letters*, Vol. 24, pp.705-713, 2003
- [13] P. M. Shankar; V. A. Dumane, J. M. Reid, V. Genis, F. Forsberg, C. W. Piccoli, B. B. Goldberg, "Classification of Ultrasonic B-mode Images of Breast Masses Using Nakagami Distribution," *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, Vol. 48, No. 2, pp.569-580, March 2001
- [14] D. Kaplan and Q. Ma, "On the Statistical Characteristics of Log-Compressed Rayleigh Signals: Theoretical Formulation and Experimental Results," *Ultrasonics Symposium*, 1993
- [15] R. C. Waag, B. A. demczar, and T. J. Case, "Nonlinear Receiver Compression Effects on the Amplitude Distribution of Backscattered Ultrasonic Signals," *IEEE Transactions on Biomedical Engineering*, vol. 38, No. 7, July 1991
- [16] S. W. Smith, R. F. Wagner, J. M. Sandrik, and H. Lopez, "Low Contrast Detectablility and Contrast/Detail Analysis in Medical Ultrasound," *IEEE Transactions on Sonics and Ultrasonics*, Vol. SU-30, No.3, pp.164-173, May 1983
- [17] M. O'Donnell, and S. D. Silverstein, "Optimum Displacement for Compound Image Generation in Medical Ultrasound," *IEEE Transactions on Ultrasonics, Ferroelectronics and frequency control*, Vol. 35, NO. 4, pp.470 – 476, July 1988
- [18] D. P. Shattuck and O. T. von Ramm, "Compound Scanning with a Phased Array," *Ultrasonic Imaging*, Vol. 4, pp.93-107, 1982

- [19] S. Jespersen, J. Wilhjelm, H. Sillesen, "Multi-angle Comounding Imaging," *Ultrasonic Imaging*, vol. 20, pp. 82-102, 1998
- [20] P. M. Shankar, "Speckle Reduction in Ultrasound B-scans Using Weighted Averaging in Spatial Compounding," *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, Vol. UFFC-33, No. 6, pp.754-758, Nov. 1996
- [21] S. Huber, M. Wagner, M. Medl and H. Czembirek, "Real-time Spatial Compounding Imaging in Breast Ultrasound," *Ultrasound in Medicine & Biology*, Vol. 28, No.2, pp.155-163, 2002
- [22] V. Behar, D. Adam, Z. Friedman, "A New Method of Spatial Compounding Imaging," *Ultrasonics*, Vol. 41, pp.377-384, 2003
- [23] F. Kallel, M. Bertrand, and J. Meunier, "Speckle motion artifact under tissue rotation," *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, vol. 41, Issue 1, pp. 105-122, Jan. 1994
- [24] Y. Li, V. L. Newhouse, P.M. Shankar and P. Karpur., "Speckle Reduction in Ultrasonic Synthetic Aperture Images", *Ultrasonics*, Vol. 30, No. 4, pp233-237, 1992
- [25] S. D. Silverstein, and M. O'Donnell, "Speckle Reduction Using Correlated Mixed-Integration Technique", *SPIE International Symposium on Pattern Recognition and Acoustical Imaging*, Vol. 768, pp.168-172, 1987
- [26] PC. Li, and M. O'Donnell, "Elevational Spatial Compounding," *Ultrasonic imaging*, Vol. 16, pp.176-189, 1994
- [27] G. E. Trahey, S. W. Smith, and O. T. von Ramm, "Speckle Pattern Correlation with Lateral Aperture Translation: Experimental results and Implications for Spatial Compounding," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. UFFC-33, No. 3, pp.257-264, May 1986
- [28] PC. Li and MJ. Chen, "A New Compounding Approach for Speckle Reduction," *IEEE Ultrasonic Symposium*, pp.1699-1702, 2000

- [29] J. E. Wilhjelm, M. S. Jensen, S. K. Jespersen, B. Sahl, and E. Falk, "Visual and Quantitative Evaluation of Selected Image Combination Schemes in Ultrasound Spatial Compound Scanning," *IEEE Transactions on Medical Imaging*, Vol. 23, No. 2, pp.181-190, Feb. 2004
- [30] M. Krueger, H. Ermert, M. Li, and H. T. Kaarmann, "Simulation of B-mode Imaging and Spatial Compounding in Inhomogeneous Media," *IEEE Ultrasonics Symposium*, pp.1385-1388, 1995
- [31] R. R. Entekin, B. A. Porter, H. H. Sillesen, A. D. Wong, P. L. Cooperberg, and C. H. Fix, "Real-Time Spatial Compound Imaging: Application to Breast, Vascular, and Musculoskeletal Ultrasound," *Seminars in Ultrasound, CT, and MRI*, Vol. 22, No. 1, pp.50-64, Feb. 2001
- [32] P. He, K. Xue, Y. Wang, "Effects of Spatial Compounding upon Image Resolution," *Proceedings of IEEE 19th International Conference on EMBS*, pp.598-600, 1997
- [33] J. M. Schmitt, "Array Detection for Speckle Reduction in Optical Coherence Microscopy," *Physics in Medicine and Biology*, Vol. 42, pp. 1427–1439, 1997
- [34] B. Tavh and M. Karaman, "Correlation Processing for Correction of Phase Distortions in Subaperture Imaging," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 40, No. 6, pp.1477-1488, Nov. 1999
- [35] S. D. Silverstein, and M. O'Donnell, "Theory of Frequency and Temporal Compounding in Coherent Imaging: Speckle Suppression and Image Resolution," *Journal of the Optical Society of America*, Vol. 5, No. 1, pp.104-113 Jan. 1985
- [36] I. Amir, N. M. Bilgutay, V. L. Newhouse, "Analysis and Comparison of Some Frequency Compounding Algorithms for the Reduction of Ultrasonic Clutter," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. UFFC-33, No. 4, pp402-411, July 1986,
- [37] R. L. Galloway, B. A. McDermott, and F. L. Thurstone, "A Frequency Diversity Process for Speckle Reduction in Real-time Ultrasonic Images," *IEEE*

- Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 35, No. 1, pp.45-49, Jan. 1988
- [38] F. Forsberg, "Assessment of Hybrid Speckle Reduction algorithms," *Physics in Medicine and Biology*, Vol. 36, No 11, pp 1539-1549, 1991
- [39] S. M. Gehlbach, and F. G. Sommer, "Frequency Diversity Speckle Processing," *Ultrasonic Imaging*, Vol. 9, pp.92-105, 1987
- [40] P.A. Magnin, O. T. von Ramm, F. L. Thurstone, "Frequency Compounding for Speckle Contrast Reduction in Phased Array Images," *Ultrasonic Imaging*, Vol. 4, pp.267-281, 1982
- [41] G. E. Trahey, J. W. Allison, S. W. Smith, O. T. von Ramm, "A Quantitative Approach to Speckle Reduction via Frequency Compounding," *Ultrasonic Imaging*, Vol. 8, pp.151-164, 1986
- [42] A. N. Evans and M. S. Nixon, "Temporal Methods for Ultrasound Speckle Reduction," IEE Seminar on Texture analysis in radar and sonar, 1993
- [43] Yan Chen, Shira L.Broschat, Patrick J. Flynn, "Phase Insensitive Homomorphic Image Processing for Speckle Reduction," *Ultrasonic Imaging*, Vol. 18, pp. 122-139, 1996
- [44] PC. Li and CL. Wu, "Strain Compounding: Spatial Resolution and Performance on Human Images," *Ultrasound in Medicine & Biology*, Vol. 27, No. 11, pp.1535-1541, 2001
- [45] F. N. Ucar, "A Speckle Suppression Technique Based on Beam-Space Processing for Medical Ultrasound Imaging," *Proceedings of IEEE Ultrasonics Symposium*, vol. 2, pp. 1703-1706, 1998
- [46] J. H. Hokland, and T. Taxt, "Ultrasound speckle reduction using harmonic oscillator models" *IEEE Transactions on Ultrasonics, Ferroelectrics and Frequency Control*, vol. 41, Issue 2, pp. 215-224, March 1994

- [47] Mustafa Karaman, Matthew O'Donnell, "Subaperture Processing for Ultrasonic Imaging," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, vol. 45, no.1, Jan 1998
- [48] R. Carotenuto, G. Loi and M. Pappalardo, "A New Extrapolation Technique for Resolution Enhancement of Pulse-Echo Imaging Systems," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 49, Mar. 2002
- [49] J. T. Ylitalo and H. Ermert, "Ultrasound Synthetic Aperture Imaging: Monostatic Approach," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 41, no. 3 May 1994
- [50] M. Karaman, PC. Li and M. O'Donnell, "Synthetic Aperture Imaging for Small Scale Systems," *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, Vol. 42, no. 3 May 1995
- [51] J. C. Bamber and C. Daft "Adaptive Filtering for Reduction of Speckle in Ultrasonic Pulse-Echo Images," *Ultrasonics*, 1986
- [52] T. Loupas, W. N. McDicken, and P. L. Allan, "An Adaptive Weighted Median Filter for Speckle Suppression in Medical Ultrasonic images," *IEEE Transactions on Circuits and Systems*, Vol. 36, No.1, Jan. 1989
- [53] A. N. Evans and M. S. Nixon, "Biased Motion-Adaptive Temporal Filtering for Speckle Reduction in Echocardiography," *IEEE Transactions on Medical Imaging*, Vol. 15, No. 1, Feb. 1996
- [54] M. Karaman, M. A. Kutay, and G. Bozdagi, "An Adaptive Speckle Suppression Filter for Medical Ultrasonic Imaging," *IEEE Transactions on Medical Imaging*, Vol. 14, no. 2 June 1995
- [55] V. Dutt and J.F. Greenleaf, "Adaptive Speckle Reduction Filter for Log-Compressed B-scan Images," *IEEE Transactions on Medical Imaging*, vol.15, no. 6, Dec 1996

- [56] J. S. Lee, "Digital Image Enhancement and Noise Filtering by Use of Local Statistics," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. PAMI-2, Mar. 1980
- [57] V. S. Frost, J. A. Stiles, K. S. Shanmugan, and J. c. Holtzman, "A Model for Radar Images and its Application to Adaptive Digital Filtering of Multiplicative Noise," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-4, Mar. 1982
- [58] D. T. Kuan, A. A. Sawchuk, T. C. Strand, and P. Chavel, "Adaptive Noise Smoothing Filter for Images with Signal-Dependent Noise," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-7, Mar. 1985
- [59] A. Lopes, R. Touzi, and E. Nezry, "Adaptive Speckle Filters and Scene Heterogeneity," *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 28, No. 6, Nov. 1990
- [60] G. Ramponi, N. Strobel, S. K. Mitra, T. Yu, "Nonlinear Unsharp Masking Methods for Image Contrast Enhancement," *Journal of Electronic Imaging*, Vol. 5, no. 3, July 1996
- [61] J. C. Bamber and J. V. Phelps, "Real-time Implementation of Coherent Speckle Suppression in B-scan Images," *Ultrasonics*, 1991
- [62] D. C. Crawford, D. S. Bell, and J. C. Bamber, "Implementation of Ultrasound Speckle Filters for Clinical Trial" *Proceedings of IEEE Ultrasonics Symposium*, vol. 3, pp. 1589-1592, Dec. 1990
- [63] A. Lopes, E. Nezry, R. Touzi, and H.Laur, "Structure Detection and Statistical Adaptive Speckle Filtering in SAR Images," *International Journal of Remote Sensing*, vol. 14, no. 9, 1993.
- [64] P. F. Stetson, F. G. Sommer, and A. Macovski, "Lesion Contrast Enhancement in Medical Ultrasound Imaging," *IEEE Transactions on Medical Imaging*, Vol. 16, No.4, Aug 1997

- [65] R. N. Czerwinski, D. L. Jones, W. D. Jr. O'Brien, "Ultrasound Speckle Reduction by Directional Median Filtering," *IEEE Proceedings International Conference on Image Processing (ICIP)*, 1995, Vol. 1, Oct. 1995
- [66] S. Ghofrani, M. R. Jahed-Motlagh and A. Ayatollahi, "An Adaptive Speckle Suppression Filter Based On Nakagami Distribution", *IEEE EUROCON'2001, International Conference on Trends in Communications*, Vol. 1, 2001
- [67] LC. Zhang, EMC. Wong, "Adaptive Speckle Reduction Based on Nakagami distribution In Medical Ultrasound Imaging," *Proceedings of the 1st International Bioengineering Conference (IBEC)*, Aug. 2004
- [68] LC. Zhang, EMC. Wong, L. M. Koh, L. S. Ng, "An adaptive filter for speckle reduction in medical ultrasound image processing," *8th Control, Automation, Robotics and Vision Conference (ICARCV)*, vol. 1, pp. 654-658, Dec, 2004
- [69] W. T. Shi, F. Forsberg, R. Bautista, C. Vecchio, R. Bernardi and B. B. Goldbeg, "Active Enhancement of Ultrasound Contrast Imaging", *IEEE Ultrasonics Symposium*, PP. 1893-1896, 2000
- [70] R. J. Collaris and A. P. G. Hoeks, "Ultrasonic B-mode Image Enhancement Based On Level-Dependent Spread Functions", *Ultrasonic Imaging*, Vol. 16, 1994
- [71] R. Kasturi, J. F. Walkup, and T. F. Krile, "Image Restoration by Transformation of Signal-Dependent Noise to Signal-Independent Noise," *Applied Optics*, Vol. 22, Nov. 1983
- [72] P. J. Burt and E. H. Adelson, "The Laplacian Pyramid as a Compact Image Code," *IEEE Transactions on Communications*, vol. COMM-31, Apr 1983
- [73] S. Ranganath, "Image Filtering using Multiresolution Representations," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 13, no. 5, May 1991.
- [74] S. Dippel. M. Stahl, R. Wiemker, T. Blaffert, "Multiscale Contrast Enhancement for Radiographies: Laplacian Pyramid versus Fast Wavelet Transform," *IEEE Transactions on Medical Imaging*, vol. 21, no. 4, April 2002

- [75] F. Sattar, L. Floreby, G. Salomonsson, and B. Lövfström, "Image Enhancement Based on a Nonlinear Multiscale Method," *IEEE Transactions on Image Processing*, Vol. 6, No. 6, June 1997
- [76] B. Aiazzi, L. Alparone, and S. Baronti, "Multiresolution Local-Statistics Speckle Filtering Based on a Ratio Laplacian Pyramid," *IEEE Transactions on GeoScience and Remote Sensing*, vol. 36, no.5, Sept 1998
- [77] B. Aiazzi, L. Alparone, S. Baronti, and G. Borri, "Pyramid-based Multiresolution Adaptive Filters for Additive and Multiplicative Image Noise," *IEEE transactions on Circuits and Systems*, vol. 45, Aug. 1998
- [78] A. N. Akansu, R. A. Haddad, *Multiresolution Signal Decomposition: Transforms, Subbands, Wavelets*, Elsevier Academic Press, 2001
- [79] R. E. Crochiere and L. R. Rabiner, *Multirate Digital Signal Processing*, Englewood Cliffs, Nj: Prentice Hall, 1983
- [80] J. Goutsias and H. J. A. M. Heijmans, "Nonlinear Multiresolution Signal Decomposition Schemes. I. Morphological Pyramids," *IEEE Transactions on Image Processing*, vol. 9, pp.1862-1876, Nov. 2000
- [81] Min Gi Kim, I. Dinstein, and L. Shaw, "A Prototype Filter Design Approach to Pyramid Generation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, pp. 1233-1240, Dec. 1993
- [82] K. Anandakumar and S. A. Kassam, "Nonlinear Multiresolution Decomposition with Applications in Image Restoration," *Journal of Electronic Imaging*, Vol. 5, no. 3, July 1996
- [83] T. Aach and D. Kunz, "Multiscale Linear /Median Hybrid Filters for Noise Reduction in Low Dose X-ray Images," *Proceedings of IEEE International Conference on Image Processing (ICIP)*, vol. II/III, pp. 358-361, 1997
- [84] J. Goutsias, "Stochastic Pyramids for Multiscale Signal Synthesis and Analysis," *Proceedings of IEEE International Conference on Image Processing (ICIP)*, vol. 1, pp. 850-854, Nov. 1994

- [85] S. Baronti, A. Casini, F. Lotti, and L. Alparone, "Content-driven Differential Encoding of an Enhanced Image Pyramid," *Signal Processing: Image Communication*, vol. 6, no. 5, 1994
- [86] K. Suzuki, I. Horiba, N. Sugie, "Neural Edge Enhancer for Supervised edge Enhancement from Noisy Images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 12, Dec. 2003
- [87] R. C. Hardie and C. G. Boncelet, "LUM Filters: A Class Rank Order Based Filters for Smoothing and Sharpening," *IEEE Transactions on Signal Processing*, vol. 41, no. 3, Mar. 1993
- [88] H. G. Longbotham and D. Eberly, "The WMMR Filters: A Class of Robust Edge Enhancers," *IEEE Transaction on Signal Processing*, vol. 41, No. 4, Apr. 1993.
- [89] F. Russo, "An Image Enhancement Technique Combining Sharpening and Noise Reduction," *IEEE Transactions on Instrumentation and Measurement*, Vol. 51, No. 4, Aug 2002
- [90] Y. H. Lee and A. T. Fam, "An Edge Gradient Enhancing Adaptive Order Statistic Filter," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. ASSP-35, May 1987.
- [91] R. C. Hardie, K. E. Barner, "Extended Permutation Filters and Their Application to Edge Enhancement," *IEEE Transactions on Image Processing*, vol. 5, no.6, June 1996
- [92] P. Perona and J. Malik, "Scale-Space and Edge Detection Using Anisotropic Diffusion," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 12, No. 7, July 1990
- [93] Y. Yu and S. T. Acton, "Speckle Reducing Anisotropic diffusion," *IEEE Transactions on Image Processing*, Vol. 11, No.11, Nov. 2002.
- [94] K. Z. Abd-Elmoniem, Abou-Bakr M. Youssef, and Y. M. Kadah, "Speckle Reduction and Coherence Enhancement in Ultrasound Imaging via Nonlinear

- Anisotropic Diffusion,” *IEEE Transactions on Biomedical Engineering*, Vol. 49, No. 9, Sep. 2002.
- [95] J. S. Suri, W. Dee, J. Gao, S. Sing, and S. Laxminarayan, “A Comparison of State-of-the-Art Diffusion Imaging Techniques for Smoothing Medical /Non-Medical Image Data”, *IEEE Proceedings 16th International Conference on Pattern Recognition*, Vol. 1, pp. 508 -511, Aug. 2002
 - [96] S. T. Acton, “Locally Monotonic Diffusion,” *IEEE Transactions on Signal Processing*, vol. 48, pp. 1379-1389, May 2000
 - [97] S. G. Mallat, “A Theory for Multiresolution Signal Decomposition: The Wavelet Representation,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, July 1989
 - [98] D. L. Donoho, “De-noising by soft thresholding,” *IEEE Transactions on Information Theory*, vol. 41, pp. 613-627, May 1995
 - [99] X. Hao, S. Gao, X. Gao, “A Novel Multiscale Nonlinear Thresholding Method for Ultrasonic Speckle Suppressing,” *IEEE Transactions on Medical Imaging*, Vol. 18, No.9, Sep. 1999
 - [100] X. Zong, A. F. Laine, and E. A. Geiser, “Speckle Reduction and Contrast Enhancement of Echocardiograms via Multiscale Nonlinear Processing,” *IEEE Transactions on Medical Imaging*, Vol. 17, no. 4, Aug. 1998
 - [101] H. Xie, L. E. Pierce, F. T. Ulaby, “SAR Speckle Reduction Using Wavelet Denoising and Markov Random Field Modeling,” *IEEE Transactions on GeoScience and Remote Sensing*, Vol. 40, No. 10, Oct. 2002
 - [102] F. Argenti, and L. Alparone, “Speckle Removal From SAR Images in the Undecimated Wavelet Domain,” *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 40, no. 11, Nov. 2002
 - [103] S. G. Chang, B. Yu, and M. Vetterli, “Spatially Adaptive Wavelet Thresholding With Context Modeling for Image Denoising,” *IEEE Transactions on Imaging Processing*, vol. 9, pp. 1522-1531, Sept. 2000

- [104] S. G. Chang, B. Yu, and M. Vetterli, "Adaptive Wavelet Thresholding for Image Denoising and Compression," *IEEE Transactions on Imaging Processing*, vol. 9, pp. 1532-1546, Sept. 2000
- [105] M. K. Mihcak, I. Kozintsev, K. Ramchandran, and P. Moulin, "Low-complexity Image Denoising Based on Statistical Modeling of Wavelet Coefficients," *IEEE Transactions on Signal Processing Letter*, vol.6 pp.300-303, Dec, 1999
- [106] M. Belge, M. E. Kilmer, and E. L. Miller, "Wavelet Domain Image Restoration with Adaptive Edge-preserving Regularization," *IEEE Transactions on Image Processing*, vol. 9, pp.597-608, Apr. 2000
- [107] Su Cheol Kang; Sang Min Lee; Seung Hong Hong, "Noise Reduction of Echocardiographic Images Using Wavelet Filtering," *Proceedings of 4th International Conference on Signal Processing Proceedings*, vol. 1, pp. 267-270, 1998.
- [108] F. N. S. Medeiros, N. D. A. Mascarenhas, R. C. P. Marques, C. M. Laprano, "Edge Preserving Wavelet Speckle Filtering," *5th IEEE Southwest Symposium on Image Analysis and Interpretation (SSIAI'02)*, 2002
- [109] Q. Zhou, L. Liu, and D. Zhang, Z. Bian, "Denoise and Contrast Enhancement of Ultrasound Speckle Image Based on Wavelet," *6th International Conference on Signal Processing*, vol. 2, pp. 1500-1503, Aug. 2002
- [110] C. Kotropoulos, X. Magnisalis, I. Pitas, M. G. Strintzis, "Nonlinear Ultrasonic Image Processing Based on Signal-Adaptive Filters and Self-Organizing Neural Networks", *IEEE Transactions on Image Processing*, Vol. 3 Issue 1 Jan.1994
- [111] D. Blacknell, C. J. Oliver, M. Warner, "Speckle Reduction of SAR Images Using Neural Networks", *IEEE Fifth International Conference on Image Processing and its Applications*, Jul 1995
- [112] Restrepo and A.C. Bovik, "Adaptive Trimmed Mean Filters For Image Restoration", *IEEE Transactions on ASSP*, Vol. 36, No.8, Aug. 1988

- [113] C. Chinrungrueng and A. Suvichakorn, "Fast Edge-Preserving Noise Reduction for Ultrasound Images," *IEEE Transactions on Nuclear Science*, Vol. 48, No. 3, June 2001
- [114] Y. Chen, R. Yin, P. Flynn, S. Broschat, "Aggressive Region Growing for Speckle Reduction in Ultrasound Images," *Pattern Recognition Letters*, Vol. 24, 2003
- [115] J. M. Park, W. J. Song and W. A. Pearlman, "Speckle Filtering of SAR Images Based Adaptive Windowing," *IEE Proceedings of Visual Image Signal Process*, Vol. 146, No. 4, Aug 1999
- [116] M. R. Zamman and C. R. Moloney, "A Comparison of Adaptive Filters for Edge Preserving Smoothing of Speckle Noise," *IEEE International Conference on Acoustics, Speech, and Signal Processing*, ICASSP-93, 1993
- [117] A. N. Evans, M. S. Nixon, "Mode Filtering to Reduce Ultrasound Speckle for Feature Extraction," *IEE Proceedings on Visual Image Signal Process*, Vol. 142, no. 2, April 1995
- [118] T. Iwai and T. Asakura, "Speckle Reduction in Coherent Information Processing," *Proceedings of the IEEE*, Volume 84, pp. 765 – 781, May 1996
- [119] G. York and Y. Kim, "Ultrasound Processing and Computing: Review and Future Directions," *Annual Review of Biomedical Engineering*, no. 01, 1999
- [120] J. Canny, "A Computational Approach to edge Detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. PAMI-8, 1986
- [121] A. C. Bovik, "On Detecting Edges in Speckle Imagery," *IEEE Transactions on Acoustics, Speech, and Processing*, Vol. 36, No. 10, Oct. 1988
- [122] R. N. Czerwinski, D. L. Jones, and W. D. O'Brien, Jr., "Line and Boundary Detection in Speckle Images", *IEEE on Transactions on Medical Imaging*, Vol. 17, No.12, Dec. 1998
- [123] V. Chalana and Y. Kim, "A Methodology for Evaluation of Boundary Detection Algorithms on Medical Images", *IEEE on Transactions on Medical Imaging*, Vol. 16, No.5, Oct. 1997

- [124] J. U. Quistgaard, "Signal Acquisition and Processing in Medical Diagnostic Ultrasound", *IEEE Signal Processing Mag.*, pp. 67-74, Jan. 1997
- [125] J. A. Jensen, "Field: A Program for Simulating Ultrasound Systems," *Med. Biol. Eng. Comp.*, *10th Nordic-Baltic Conference on Biomedical Imaging*, Vol. 4, Supplement 1, Part 1:351–353, 1996
- [126] M. M. Hadhoud and D. W. Thomas, "The Two-Dimensional Adaptive LMS (TDLMS) Algorithm," *IEEE Transactions on Circuits and Systems*, Vol. 35, No. 5, May 1988
- [127] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image Quality Assessment: From Error Visibility to Structural Similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, Apr. 2004
- [128] Angelsen and Bjorn, *Ultrasound Imaging : Waves, Signals, and Signal processing*, Emantec, 2000
- [129] Rumack and M. Carol, *Diagnostic Ultrasound*, Mosby, 1998
- [130] R. Haralick and L. Shapiro, *Computer and Robot Vision*, Addison-Wesley Publishing Company, 1992
- [131] R. Schalkoff, *Digital Image Processing and Computer Vision*, John Wiley & Sons, 1989
- [132] J. S. Lim, *Two-Dimensional Signal and Image Processing*, Prentice Hall, Englewood Cliffs, NJ, 1990
- [133] S. Haykin, *Adaptive Filter Theory*, Prentice Hall, 1997