A Study on Speckle Noise Reduction and Feature Extraction in Ultrasonic Images

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Abstract— Ultrasonic image is one of the imaging techniques that widely used and safe for medical diagnostic, due to its noninvasive, low cost and real time forming. However, the qualities of ultrasonic images are typically degraded mainly due to the presence of signal independent known as speckle noise. In this paper, speckle noise suppression in wavelet domain and feature extraction technique is studied. In particular, speckle noise reduction is a preprocessing step before applying a feature extraction process. In speckle noise suppression process, the logarithmic transform is firstly applied to the original image in order to convert multiplicative noise to additive one. 2D Stationary Wavelet Transform (SWT) is used to decompose the logarithmic image into four subbands. Next, 2D adaptive Wiener Filter is applied all over areas only in detail subbands. Finally, the 2D Inverse SWT is computed and it is followed by the exponential transform to get the reconstructed image. To evaluate the studied method for speckle noise reduction, some classical well-know methods, such as Median filter, Wiener filter, Discrete Wavelet Transform (DWT) based on Soft thresholding and DWT along with Wiener filter are compared. For feature extraction process, Haar wavelet filter is used to extract the ultrasonic features compared with Sobel and Canny operator. Moreover, the nonmaxima suppression technique is adopted to get the edge localization. Finally, the hysteresis thresholding is applied to get the final result in binary format. The results have clearly demonstrated that the studied method outperforms several existing methods for speckle noise reduction in terms of signal to mse ratio (S/mse) and edge preservation (β). Moreover, the studied method can detect well-localized and thin edges.

Keywords **-** Feature Extraction, Speckle Noise Reduction, Stationary Wavelet Transform, Ultrasonic Images.

I. INTRODUCTION

Ultrasound imaging is widely used and plays an important role in medical diagnosis because it is a noninvasive, real-time and inexpensive modality [1]. However, ultrasonic images are usually suffered from speckle noise, which corresponds to coherent wave interference in tissue. It is well known to be signal-dependent in ultrasound imaging system. Over the years, speckle noise suppression and feature extraction have been widely studied and considered. When filtering random noise from a noisy image, two main issues to be considered are: 1) how much noise had been removed, and 2) how well edges are preserved without blurring. Conventionally, there are several simple techniques for speckle noise suppression. Some of well-known classical speckle filterings include Lee filter, Kuan filter, Median filter and homomorphic Wiener filters [2-5]. They can effectively suppress speckle noise but they fail to adequately preserve the edges. In the past decade, there had been considerable interest in using the Wavelet transform as a powerful tool for recovering signal from noisy data. This method is generally referred to as wavelet shrinkage technique. In 1995, D. L. Donoho presented a soft thresholding method for denoising in one dimensional signal [6]. S. Chang, B. Yu and M. Vetterli introduced a new shringkage method, BaeyShrink [7], which also outperformed Donoho and Johnstone's Sureshrink [8]. Furthermore, others proposed probabilistic methods for speckle noise reduction in the wavelet domain [9]-[12]. Another proposed approach uses adaptive block-based singular value decomposition for speckle noise suppression [13]. Recently, A. K. Gupta and D. Sain have proposed a speckle reduction technique using logarithmic threshold contourlet [14]. The method proposed by C. Barcelos and L. Vieira used an adaptive edge-controlled variation function to detect and reduce speckle noise [15]. Moreover, speckle noise suppression and feature extraction in ultrasonic images is proposed [16].

In this research, a method for speckle reduction and feature extraction in ultrasonic images is studied. First, a logarithm is applied to the original image in order to transform the multiplicative noise into the additive noise. Next, a 2D Stationary wavelet transform (SWT) is used to decompose the image result from the first step into four subbands. Then, 2D adaptive Wiener filter is applied over areas only in detailed subbands. Finally, an inverse 2D SWT is computed and applied the exponential transform to reconstruct the image. The studied method is also compared with some existing approaches, such as Median filter, Wiener filter, 2D Discrete Wavelet Transform (DWT) based on Soft thresholding and DWT along with Wiener filter. Speckle noise reduction is a preprocessing step before applying a feature extraction process. Next, feature extraction process, Haar wavelet filter is used to extract the ultrasonic features compared with Sobel and Canny operator. Moreover, the nonmaxima suppression technique is adopted to get the edge localization. Finally, the hysteresis thresholding is applied to get the final result in binary format.

The rest of this paper is organized as follows. Section II describes the study of speckle noise reduction, feature extraction and quantitative image quality measures. Also, the experimental results are expressed in section III. Finally, the conclusion is provided in section IV.

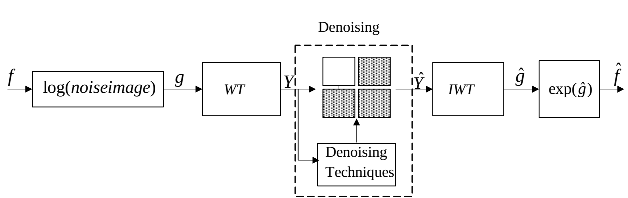


Figure 1. Block diagram for speckle noise reduction

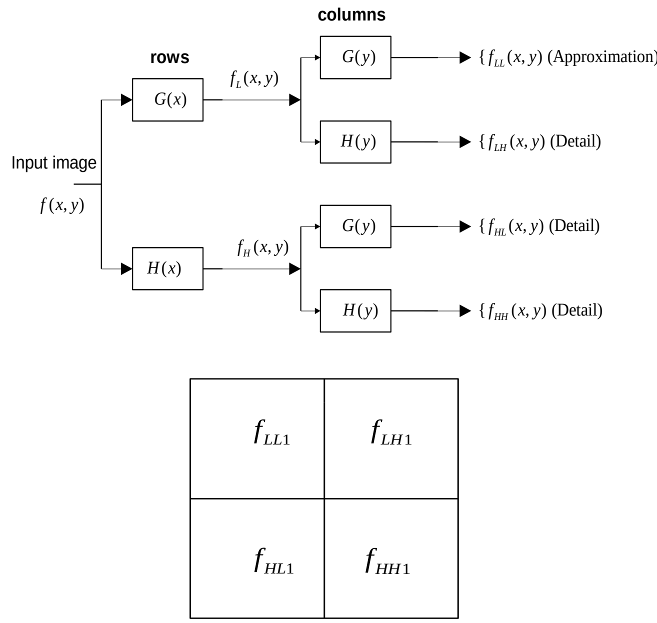


Figure 2. 2D Stationary Wavelet Transform Decomposition Scheme

II. Research Methodology

A. *Speckle noise reduction and feature extraction*

Similar to homomorphic Wiener filtering, the studied method can develop a speckle noise reduction, which is done in the SWT domain. The block diagram of the studied method is illustrated in Fig. 1. Details are as follows [16]:

a) Take a logarithmic transform to the original image (f), which yields image result (g).

b) Perform a 2-D SWT of the log transformed image and decompose into four subbands (LL, LH, HL and HH).

c) Perform a 2-D adaptive Wiener filter only in the detailed subbands (LH, HL and HH), window size 7x7 is chosen, which yields the image result ($\hat{Y}$).

d) Apply the inverse 2-D SWT, which yields a denoised image ($\hat{g}$).

e) Take the exponential transformation of the denoised image to get the reconstructed image ($\hat{f}$).

1) *2D Stationary Wavelet Transform*

Unlike the conventional Discrete Wavelet Transform (DWT), the two dimensional Stationary Wavelet

Transform (2D SWT) is based on the idea of no decimation, which means the SWT is translation-invariant [17]. It applies the DWT and omits both down-sampling in the forward and up-sampling in the inverse transformation. 2D SWT can be implemented by first applying the DWT along the rows of an image, and then applying it on the column of an image. Therefore, a transformed image is decomposed into four subbands, which are the same size as the original image. The LL band contains the approximation coefficients, the LH band contains the horizontal details, the HL band contains the vertical details and the HH band contains the diagonal details. Without translation-invariance, slight shifts in the input signal will produce variations in the wavelet coefficients that might introduce artifacts into the noise reduction process. This property is good for noise removal because the noise is usually spread over a small number of neighboring pixels. The 2D SWT decomposition scheme is illustrated in Fig 2.

2) 2D Adaptive Wiener Filter

Two dimensional Wiener filter is a minimum mean-square error filter [18]. It is a nonlinear spatial filter that moves a window or kernel over each pixel in the image, computing and replacing the central pixel values under the window. It uses a neighborhood of window sizes to estimate the noise power from the local image mean (μ) and standard deviation (σ). 2-D Wiener filter has output defined by [19-20],

$$\hat{Y}(x_i, y_j) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(Y(x_i, y_j) - \mu) \qquad (1)$$

where μ, σ^2 represents the local mean, standard deviation obtained from the noisy image window respectively. Y is the noisy pixel and $\hat{Y}$ is the filtered pixel. Also, v is the noise variance, estimated from the average of all the local estimated variances in the image. The size of the kernel should be odd. If the size is too large, important features will be lost. On the other hand, if the size is too small, noise reduction may not yield good results. In general, a size 3x3 and 7x7 kernel provides good results [14].

3) Feature extraction

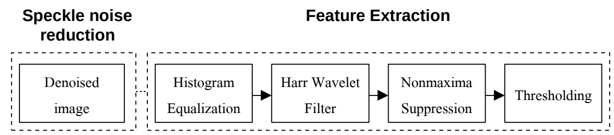


Figure 3. Block diagram for feature extraction process [16]

Fig. 3 shows the feature extraction process. First, the denoised image is enhanced by histogram equalization technique where the accumulative histogram of the image is linear [2]. The goal of this method is to make structure within the image more visible to human observers. Next, Haar filter is used to extract the object from denoised images in the vertical and horizontal direction separately and modulus sum is used to get the edge detection result. Then, nonmaxima suppression technique is adopted to get the edge localization. Finally, the adaptive hysteresis thresholding is applied to get the final result in the binary format. In a binary image, each pixel value is represented by a single binary format.

B. Quantitative quality measures

To quantify the achieved noise reduction ability performance, there are two main issues to be considered, which are how much noise has been removed, and how well edges are preserved without blurring. In the past decade, there have been many quantitative quality measurements proposed. In this research study, three image quality measurements: Mean Square Error (*MSE*), Signal to MSE ratio (*S/mse*), and edge preservation (β) are used and computed using original and reconstructed image data [21-22].

1) Mean Square Error (MSE)

$$MSE = \frac{1}{mn}\sum_{i,j=1}^{m,n}\left(\hat{s}_{i,j} - s_{i,j}\right)^2 \qquad (2)$$

Whereas n and m are image size, $\hat{S}$ and S refer to reconstructed and original images, respectively. The higher MSE values denote lower image quality.

2) Signal to MSE ratio (S/mse)

To evaluate speckle noise reduction, a Signal to MSE ratio (S/mse) is used, instead of the standard signal to noise ratio. This is defined as below:

$$\beta = \frac{\Gamma\left(\Delta s - \overline{\Delta s}, \Delta\hat{s} - \overline{\Delta\hat{s}}\right)}{\sqrt{\Gamma\left(\Delta s - \overline{\Delta s}, \Delta s - \overline{\Delta s}\right).\Gamma\left(\Delta\hat{s} - \overline{\Delta\hat{s}}, \Delta\hat{s} - \overline{\Delta\hat{s}}\right)}} \quad (3)$$

where $\overline{\Delta s}$ and $\overline{\Delta\hat{s}}$ are the mean values in the region of interest (ROI) $s_{i,j}$ and $\hat{s}_{i,j}$, respectively. Also, Δs and $\Delta\hat{s}$ represent the high pass filtered operation of s and $\hat{s}$ respectively, obtained with a 3x3 pixel standard approximation of Laplacian operator with

$$\Gamma(s_1, s_2) = \sum_{i,j=1}^{m,n} s_{1(i,j)} \cdot s_{2(i,j)} \quad (4)$$

The larger values of β signify the better feature preservation ability of the reconstructed image.

III. Experimental results

A. *Speckle noise reduction*

Speckle noise reduction is a preprocessing step before applying a feature extraction process. In this part of the experiment, to validate the performance of the studied method, various liver ultrasonic images are used, as shown in Fig. 4. The image size is 256x256. A number of experiments were conducted and compared with other traditional methods, which were Median filter (7x7), 2D adaptive Wiener filter (7x7), DWT with soft thresholding, and DWT along with Wiener filter. The experiments reported in this section have been tested using MATLAB 10.0 – R2010b (64 bit). All the wavelet-based techniques used Daubechies 4 wavelet basis, with one level of DWT and SWT decomposition. In fact, noise is generally spread over in detailed subbands, due to the components of highpass wavelet filters. Therefore, the 2D adaptive Wiener filter is applied only in detailed subbands. To quantify the achieved performance in terms of the ability of speckle noise reduction and edge preservation, the original liver ultrasonic images are corrupted with noise at variance 0.08. S/mse and β are used to evaluate the reconstructed image quality. The results are tabulated in Table I. As can be seen, the studied method outperforms other methods in terms of S/mse and β.

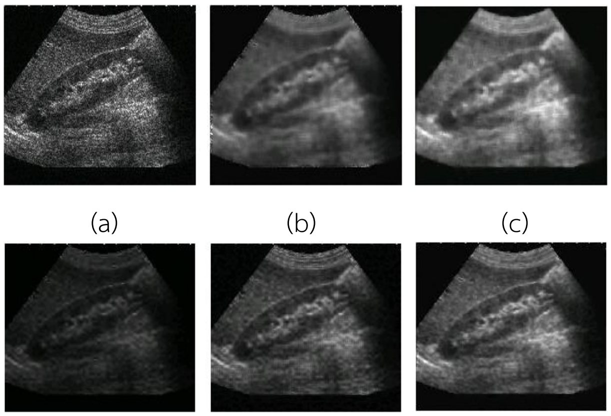
To visually compare with all other methods, the original kidney ultrasonic images are corrupted with noise at variance 0.08 as shown in Fig. 5 (a). The comparatives of various results are also shown in Fig. 5 (b)-(f). As for the results, Fig. 5(b) and Fig. 5(c) are operated by a fixed 7x7 sized window using Median filter and Wiener filter respectively in a special domain. The reconstructed images are smoothed over and have artifacts around the object. On the other hand, the combination of Wiener filter and SWT outperforms DWT with soft thresholding and DWT along with Wiener filter, as shown in Fig. 5(d), (e) and (f). It can efficiently reduce noise and smooth over the homogeneous area. In addition, it can preserve the edge features whereby enhancing the visual perception of the reconstructed image.

B. *Feature extraction*

Next experiments, the realistic noisy uterus and cholecystitis ultrasonic images are tested, as shown in Fig. 6(a) and Fig. 7(a), respectively. The denoised images and enhancement results using studied method are expressed in Fig. 6(b)-(c) and Fig. 7(b)-(c). In the feature extraction process, Haar wavelet filter is used for feature extraction pointed out by an ultrasonographer [23]. In fact, gray level is important information for diagnosis and Haar wavelet filter seemed to be able to preserve original gray level after feature extraction. This thin edge detected image with preserved gray level is important information for diagnosis because gray level expresses power of reflected signal. Consequently, the ratio of sound velocity at tissue-tissue-interface from the gray level can be identified, which may mean elasticity of tissue. As a result, Fig. 6(d,e,f) and Fig. 7(d,e,f) are performed by applying Sobel operator, Canny operator, and the proposed method, respectively, to derive the edge feature. It can be seen that the studied method leads to an effective method for speckle noise reduction and yields the best result for feature extraction.

(a) (b) (c)

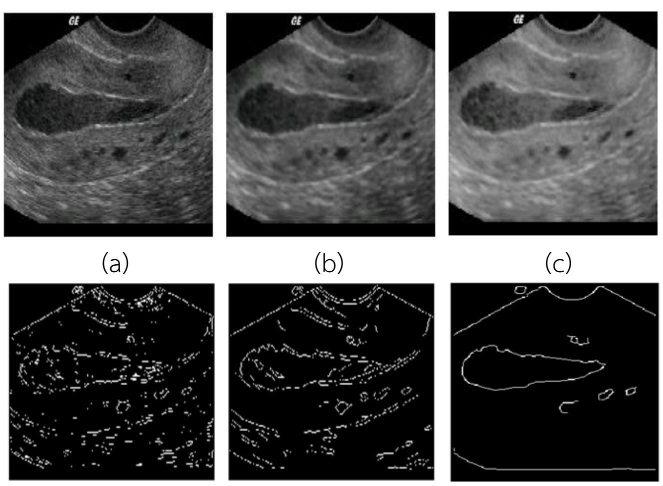
Figure 4. Liver ultrasound images



(a) (b) (c)

(d) (e) (f)

Figure 5. Results of various speckle reduction methods (a) noisy kidney ultrasound image (b) denoised image using 2D Median filter (c) denoised image using 2D Wiener filter (d) denoised image using Visushink and Soft thresholding (e) denoised image using DWT and Wiener filter (f) denoised image using SWT and Wiener filter



(a) (b) (c)

(d) (e) (f)

Figure 6. Results of various feature extraction methods (a) noisy uterus ultrasound image (b) denoised image using SWT and Wiener filter (c) enhanced image (d) Sobel operator (e) Canny operator (f) Studied method

TABLE I EXPERIMRNTAL RESULTS AT NOISE VARIANCES 0.08

Images	Methods	Mask size	S/mse	β
liver (a)	Median filtering	7x7	17.014	0.0502
	Wiener filtering	7x7	17.047	0.1704
	Visushink with Soft thresholding	-	17.613	0.2441
	DWT and Wiener filter	7x7	17.375	0.2135
	SWT and Wiener filter	7x7	18.166	0.3089
liver (b)	Median filtering	7x7	9.7961	0.0504
	Wiener filtering	7x7	12.971	0.7636
	Visushink with Soft thresholding	-	12.799	0.6505
	DWT and Wiener filter	7x7	13.505	0.7117
	SWT and Wiener filter	7x7	14.113	0.7801
liver (c)	Median filtering	7x7	15.076	0.2351
	Wiener filtering	7x7	15.482	0.3650
	Visushink with Soft thresholding	-	14.991	0.3205
	DWT and Wiener filter	7x7	15.918	0.3356
	SWT and Wiener filter	7x7	16.868	0.4359

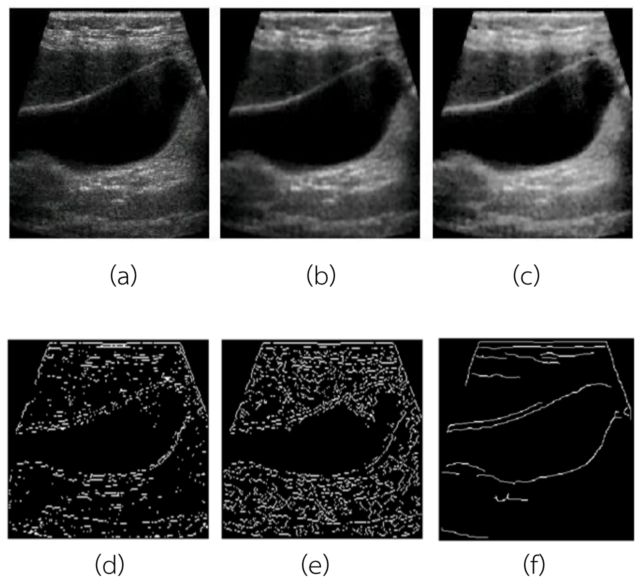


Figure 7. Results of various feature extraction methods
(a) noisy cholecystitis ultrasound image
(b) denoised image using SWT and Wiener filter
(c) enhanced image (d) Sobel operator
(e) Canny operator (f) Studied method

IV. Conclusion

In this research, the main aim is to study and compare the different methods of speckle noise suppression and feature extraction in ultrasonic images. For speckle noise reduction, the studied method uses SWT to transform a logarithmic image and then applies an adaptive Wiener filter only in each detail subband. The advantage of multiresolution analysis using SWT for speckle noise reduction is that it can reduce noise while preserving the feature structure of the reconstructed image. From the results, the combination of the SWT and adaptive Wiener filter has better quantitative and qualitative performances, compared with existing methods. For feature extraction process, the denoised image is enhanced by histogram equalization. Haar wavelet filter is used for feature extraction. From the results, the studied method compared with Sobel operator and Canny operator can be detected well-localized and thin edges. Therefore, the studied method leads to a practical method for speckle noise reduction and feature extraction in ultrasonic images.

References

[1] A. Webb and G. C. Kagadis, "Introduction to biomedical imaging," Wiley Hoboken, 2003.

[2] A. Mcandrew, "Introduction to digital image processing with MATLAB," Course Technology, ISBN-10 534400116, 2004.

[3] J. S. Lee, "Digital image enhancement and noise filtering by use of local statistics," IEEE Transactions on Pattern Analysis and Machine Intelligence, no. 2, 1980, pp. 165–168.

[4] 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, no. 2, 1985, pp. 165–177.

[5] A. K. Jain, "Fundamentals of digital image processing," Prentice-Hall Englewood Cliffs, 1989.

[6] D. L. Donoho, "De-noising by soft-thresholding," IEEE Transactions on Information Theory, vol. 41, no. 3, 1995, pp. 613–627.

[7] S. G. Chang, B. Yu, and M. Vetterli, "Adaptive wavelet thresholding for image denoising and compression," IEEE Transactions on Image Processing, vol. 9, no. 9, 2000, pp. 1532–1546.

[8] D. L. Donoho and J. M. Johnstone, "Ideal spatial adaptation by wavelet shrinkage," Biometrika, vol. 81, no. 3, 1994, pp. 425–455.

[9] P. Kishore, A. Sastry, A. Kartheek, and S. H. Mahatha, "Block based thresholding in wavelet domain for denoising ultrasound medical images," International Conference in Signal Processing And Communication Engineering Systems (SPACES), 2015, pp. 265–269.

[10] J. Jin, Y. Liu, Q. Wang, and S. Yi, "Ultrasonic speckle reduction based on soft thresholding in quaternion wavelet domain," Instrumentation and Measurement Technology Conference (I2MTC), 2012, pp. 13–16.

[11] C. Chen and N. Zhou, "A new wavelet hard threshold to process image with strong gaussian noise," International Conference in Advanced Computational Intelligence (ICACI), 2012, pp. 558–561.

[12] J. Scharcanski, C. R. Jung, and R. T. Clarke, "Adaptive image denoising using scale and space consistency," IEEE

Transactions on Image Processing, vol. 11, no. 9, 2002, pp. 1092–1101.

[13] N. Sae-Bae and S. Udomhunsakul, “Despeckling algorithm on ultrasonic image using adaptive block-based singular value decomposition,” in Photonics Asia 2007, International Society for Optics and Photonics, 2007, pp. 68 330J–68 330J.

[14] A. K. Gupta and D. Sain, “Speckle noise reduction using logarithmic threshold contourlet,” International Conference in Green Computing, Communication and Conservation of Energy (ICGCE), 2013, pp. 291–295.

[15] C. A. Barcelos and L. E. Vieira, “Ultrasound speckle noise reduction via an adaptive edge-controlled variational method,” International Conference in Systems, Man and Cybernetics (SMC), 2014, pp. 145–151.

[16] S. Udomhunsakul and P. Wongsita, “Feature extraction in medical ultrasonic image,” in 3rd Kuala Lumpur International Conference on Biomedical Engineering 2006, ser. IFMBE Proceedings, F. Ibrahim, N. Osman, J. Usman, and N. Kadri, Eds. Springer Berlin Heidelberg, vol. 15, 2007, pp. 267–270.

[17] G. P. Nason and B. W. Silverman, “The stationary wavelet transform and some statistical applications,” in Wavelets and statistics, Springer, 1995, pp. 281–299.

[18] J. S. Lim, “Two-dimensional signal and image processing,” Englewood Cliffs, NJ, Prentice Hall, 1990.

[19] D. Lai, N. Rao, C. H. Kuo, S. Bhatt, and V. Dogra, “An ultrasound image despeckling method using independent component analysis,” International Symposium in Biomedical Imaging: From Nano to Macro, 2009, pp. 658–661.

[20] E. Ercelebi and S. Koc, “Lifting-based wavelet domain adaptive wiener filter for image enhancement,” IEE Proceedings-Vision, Image and Signal Processing, vol. 153, no. 1, 2006, pp. 31–36.

[21] A. Achim, A. Bezerianos, and P. Tsakalides, “Novel bayesian multiscale method for speckle removal in medical ultrasound images,” IEEE Transactions on Medical Imaging, vol. 20, no. 8, 2001, pp. 772–783.

[22] F. Sattar, L. Floreby, G. Salomonsson, and B. Lovstrom, “Image enhancement based on a nonlinear multiscale method.” IEEE transactions on image processing, vol. 6, no. 6, 1996, pp. 888–895.

[23] S. Udomhunsakul and K. Hamamoto, “Blood vessel diameter measurement on ultrasonic images,” Proceedings of the SPIE, Vol. 5637, 2005, pp. 113-117.