SPECKLE NOISE REDUCTION USING MULTISCALE LMMSE (MLMMSE)-BASED FILTER

By

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FINAL PROJECT REPORT

Submitted to the Department of Electrical & Electronic Engineering in Partial Fulfillment of the Requirements for the Degree Bachelor of Engineering (Hons) (Electrical & Electronic Engineering)

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CERTIFICATION OF APPROVAL

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A project dissertation submitted to the Department of Electrical & Electronic Engineering Universiti Teknologi PETRONAS in partial fulfilment of the requirement for the Bachelor of Engineering (Hons) (Electrical & Electronic Engineering)

Approved:

Ms Norashikin Yahya Project Supervisor

UNIVERSITI TEKNOLOGI PETRONAS TRONOH, PERAK

MAY 2013

CERTIFICATION OF ORIGINALITY

This is to certify that I am responsible for the work submitted in this project, that the original work is my own except as specified in the references and acknowledgements, and that the original work contained herein have not been undertaken or done by unspecified sources or persons.

Mohd Zulfadzlie Bin Zainal Abidin

ABSTRACT

This report presents the project of studying the speckle noise reduction using Multiscale Least Minimum Mean Square Error (MLMMSE) filter. The MLMMSE filter is being compared in terms of feasibility, dependency and stability with the conventional image filter such as LEE 3X3, LEE 5X5, LEE 7X7 and Median filter. The estimation of the MLMMSE filter scheme for the image denoising is being proposed. Together with this project the wavelet selection to determine the best wavelet suit with MLMMSE filter is also being discussed. The principle of the speckle reduction is being used as the MLMMSE filtering are being perform with an undecimated domain wavelet. The image of the adaptive noise will be rescaling from the detail coefficient whereby the amplitude of the image signal will be divided with the variance ratio from the noisy image coefficient to the denoise image. This image is calculated analytically using the properties from the noisy image together with varying the variance and the selected optimal wavelet only. The original image is not resorting in order to obtain the result or to assessing the underlying backscattered signal. Experiment is carried out on normal image being test within two parameter that is Structural Similarity Index (SSIM) and Peak Signal Noise Ratio (PSNR) with varying the variance and the wavelet to identify the most suitable wavelet to run with MLMMSE filter for ultrasound images. The equivalent number of looks (ENL) is analysed in the last part of the experiment to demonstrate visual image quality is achieved for excellency in terms of the dependency of the images itself and also to avoid the typical of impairments of the images which normally created from the critically subsampled in the wavelet-based image denoising.

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LIST OF ABBREVIATIONS

1.MLMMSE	 Multiscale Least Minimum Mean Square Error
2.US	– Ultrasound
3.CT	- Computerized Tomography
4.Rad	– Radian
5.2-D	– Two Dimension
6.DTCWT	– Dual Tree Complex Wavelet Transform
7.DWT	– Discrete Wavelet Transform
8.PSNR	– Peak Signal To Noise Ratio
9.SSIM	– Structural Similarity Index
10.ENL	– Equivalent Number Of Looks

CHAPTER 1 INTRODUCTION

1.1 Project Background

Ultrasound can be defined as a cyclic sound high pressure wave where its frequency is beyond human hearing region. It is cannot be separated from the normal audible sound in term of its physical properties but it just human not be able to hear it. Human can hear things up to 20 Kilohertz where ultrasound operates from 20Kilohertz to several Gigahertz as shown in Figure 1. Ultrasound was found in 1942 and being widely use since, in many field. For example in medical application, ultrasound is use to show the image of a developed baby in the mother's womb.

Ultrasound imaging or sonography, the tissue, muscle, and internal organ were viewed by using high-frequency sound waves. Since the ultrasound imaging is processed in real indicating-timing mode, it have been showed the action of the inside organ of our body and also the blood that flows. During the ultrasound process, hand-held transducers were placed on the skin. This transducer is use in sending out the high frequency wave that will reflect in the internal body. It will produce the sound waves that will be referred on display monitor. This image quality will be selected upon the amplitude mode and frequency mode of the signal of sound and how long it take to return their transducer.

An ultrasound machine provides the images which will be allowing the numerous organs in human body can be examined in a short time. This machine will be sending out the high-frequency of the sound waves where it which will be reflecting the body diagram or structure. There will be a computer in order to accept or receives the waves that being reflected where it will utilise them to snap or creating the picture. The ultrasound is different to an x-ray or CT scan because of in ultrasound system there will be no ionizing radiation will be exposed during the system run.

There are a lot of type of ultrasound being use in the medical process some are :-

-Doppling of ultrasound. (show blood flow in the blood vessel)

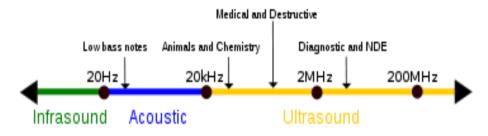
-Sonography of animal and human bone. (to analyse bone bad symptom)

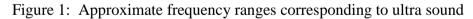
-The echocardiogram. (to visualize human and animal heart)

-The ultrasound for fetal.

(to show the fetus status)

The doppling of heart failure.(analysing the unstable heart beat)





1.2 Problem Statement

In this research, the ultrasound imaging system being focused as in medical ultrasound image a lot of images result being affected by speckle phenomenon. Ultrasound images is not fully enhanced during the process run where it have the speckle effect where the speckle effect happen because of coherent processing of the return backscattered signals. In this system, the speckle or noise can be reduced by improving the acquired hardware. Unfortunately in ultrasound imaging the speckle is formed during the image acquisition process so this image had to be processed by some noise removal technique before any subsequent image processing operates.

1.3 Objectives

The main objectives for this project includes :-

- 1.)Developing MLMMSE filter for removal of multiplicative speckle noise in ultrasound imaging process.
- 2.)Analysing the performance of MLMMSE filter using different type of wavelet.
- 3.)To compare the performance of MLMMSE filter with Lee, Median filter using simulated data.
- 4.)To compare the result of MLMMSE, Lee, and Median filter by using real ultrasound images.

1.4 The Scope Of Study

The main area scope study of this project are :

- 1.)Experiment design to evaluate the performance of the noise reduction filters using simulated data, for example a clean image is artificially corrupted with speckle noise.
- 2.) Develop MATLAB code for LMMSE-based speckle noise reduction.
- 3.) Run the experiment with several test images at different level of noise variance
- 4.) Run the experiment with real noisy ultrasound images.

1.5 Project Feasibility

The feasibility of this project is very acceptable since the tool needed for this project and all equipment facilities such as MATLAB software are provided in this University Teknologi Petronas. Thus with planner on Gantt Chart and the proposed methodology, we are to complete all the research experiment within the time frame.

CHAPTER 2 LITERATURE REVIEW

2.1 Speckle

The ultrasound imaging in medical ultrasound application is resulting in a blurry images due to some of the speckle availability. Ever since known, speckle is a kind of cumulative noise where it decrease the natural situation of the ultrasound images and also its affected the feasibility of the human while dealing with it.

This kind of technic is quite effective in reducing speckle but its involving hardware to upgrade which is very expensive. Due to this matter, a lot of other attempt of the alternative processing of alternative algorithms, including Median, Lee[1], Frost[2] and Kuan [3] filtering techniques being brought by the researcher in instant. Unfortunately all of this conventional noise filtering methods normally resulting still the unclear or blur imaging[4].

Recent found by the researcher, the new filtering line of wavelet transform has been use as a resourceful tool in recovering the bad signal process. They are reason behind this in using this multiscale post-decomposition technique which is, the analysing statistics which result to more natural in signalling. This is because when the signal is decomposed by using the wavelet basis, the signal is becoming simple in arrangement. Furthermore, when the signal is employ with this multiscale technique they found that the noises are able to be processed at different scales of signal component. Earlier method to reduce speckle noise is by arranging the incoherent ultrasound images stand under the same body was analyzed within the differential place[5]. In this work, we will investigate the capability of multiscale LMMSE-based filter in reducing speckle noise in ultrasound images. The performance of the filter will be compared with other conventional filters such as Lee and Median filter.

As the LMMSE filter was developed in the framework of additive white noise, applying to speckle noise would require ultrasound imaging to work in homomorphic framework. This is because the speckle effect in ultrasound images is a type of multiplicative noise so by applying logarithmic transform, it will convert the multiplicative model to additive model.

2.2 Statistical Characteristics Of Speckle Noise

As being found and discuss by the researcher, speckle is known that it is the result from addition and destruction of the backscattered of coherent wave. Thus, the speckle usually happen in unstable of the element cell of the bad scatterers. To further explain, there are normally a lot of scatterer that will gone to the element cell where at a time they will receive some phase. This scatterers then will eventually channeling signal numbered begin with 0 to 2π rad. The signal amplitude of the uncoherent waves is basis on the Rayleigh function of probability density that is ; [1]

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$$p(A_s) = \frac{A_s}{\sigma^2} exp\left(-\frac{A_s}{2\sigma^2}\right)$$

Rayleigh (1)

where the A_s bigger than 0 and $p(A_s)$ equal to 0 and for A_s is less than 0. In the calculations of pre-order average the A_s average value will calculated as sigma component, the result is the speckle or noise will act as an additional noise. In this case the speckle will be decreased together with N independent of the sample image. A_s then will be getting the N completed convolution of equation (1)[6]. There are a best way to convert the noise into the additional one which by applying the logarithmic equation to the noise. When this noise being applied with the logarithmic equation, the noise will automatically transform to the Gaussian White additive noise. The j in the equation is the parameter of scaling and it change in its value.

2.3 Dual Three Complex Waveform

The wavelet that will be used in this experiment is dual-tree complex wavelet transform. This wavelet will be transferring the signal of the decomposition to the nature of the function. This wavelet is being created according to dilation (DTCWT) and translation for the known of mother wavelet $\psi(x)$. In the scaling function of $\varphi(x)$, the mother wavelet is being created. Mallat et al had state that in the discrete wavelet transform (DWT) the filter bank in normal coefficient will be using the $\psi(x)$ and $\varphi(x)$ coefficient. The dual tree wavelet is now found as the further use of the DWT in signalling image processing.[7]

Based on the recent coefficient the DTCWT will be taken as the summation of two DWTs. This DWTs will be creating the real and imaginary part of the DTCWT. The DWTs will be joined in together in order to perform the analytic transform in the overall process. At this state, the collective of DWTs from two of them are now completed the system. The 2-D wavelet transform will be created or collaborated as being visualize from Figure 2. This DTCWT expanded up to four time of its expansion and will greatly cooperate for achieving a good additional unlikely the 2-D

DWT which cannot perform it. The DTCWT is mostly in changing invariant but with the appropriate directional. The 2-D DWT will be directional into 3 channel with weak channel selection for diagonal. In contrast, the 2-D DTCWT have with them 2 dimensional of 12 directional wavelet with oriented angle of $\pm 75^{\circ}$, $\pm 45^{\circ}$, and $\pm 15^{\circ}$ [8].

The transformation is being used in conjunction of reducing the noise in the algorithm of the images. Its increase the characteristic of the wavelet 2-D DTCWT makes it being use a lot in the image processing world. This is why the signal and the noise now can be seperated into totally different component without having major problem. Because of the subband approximation coefficient resulting in a lot of signal information, they will be untouched by any wavelet coefficient and later applied with subband coefficient. Wavelet transform is being called as in a straight or linear system so it will resulting in twelve list detail subband on their very level after the process image was decompose.

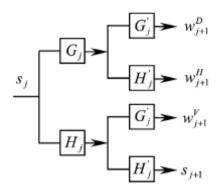


Figure 2: 2-D at first level. [9][10]

2.4 LMMSE Of Wavelet Coefficient

The *f* which is the original being corrupted together with the Gaussian White additive noise ε ;

$$g = f + \varepsilon$$

which $\varepsilon \in N(0, \sigma^2)$. Then the OWE will be applied for signal of noise at g_j on the j_j which getting ;

$$w_j = x_j + v_j$$

which w_j become coefficient on $j_i x_j$ and v_j are further expand of f and ε . LMMSE wavelet coefficient being perform. Since x_j also v_j mean is zero, LMMSE for x_j is[11];

$$\hat{x}_j = c' \cdot w_j$$

and;

$$c = \frac{\sigma_{x_j}^2}{\sigma_{x_j}^2 + \sigma_j^2}$$

Here, the noise deviation for v_j on the j_j scalling for every channel directional yields ;

$$\sigma_j = ||L_{j-1}||\sigma$$

which L_{j} -1 be the further filter of $(L_{j-1}^{D}, L_{j-1}^{H} \text{ or } L_{j-1}^{V}) \| \cdot \|$ be the coefficient of $\|L\| = \sqrt{\sum_{l} \sum_{k} L^{2}(l, k)}$. The original of the deviation $\sigma_{x_{j}}^{2}$ for the image without noise, x_{j} be as

below[11];

$$\hat{\sigma}_{x_j}^2 = \sigma_{w_j}^2 - \sigma_j^2$$

with;

$$\sigma_{w_j}^2 = \frac{1}{M\cdot N}\sum_{m=1}^M\sum_{n=1}^N w_j^2(m,n)$$

Here M and N conducting its number for image input in row and also the column. The wavelet LMMSE can be described as equal to soft threshold significantly. At this time the factor of C now being always smaller than 1 and make the magnitude of x_j become lesser than w_j . The energy is decreasing from this phenomenon of a restored signal same in what is happening soft threshoding. Good enhanced result will be achieved as LMMSE wavelet coefficient been given by [9] and [10] which leads in utilizing the effectiveness of dependency for wavelet intrascale.

CHAPTER 3 METHODOLOGY

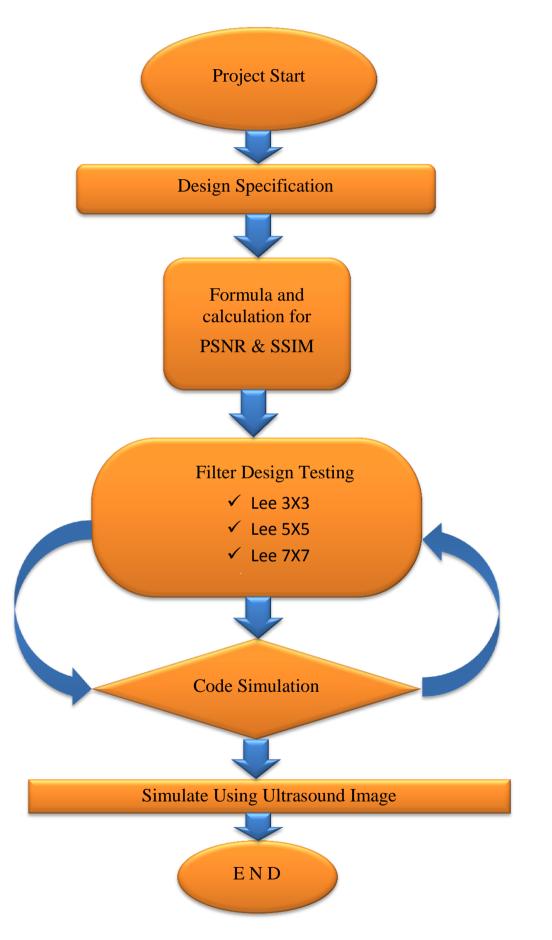
3.1 Project Methodology

In this research we use MATLAB to simulate ultrasound noise or speckle remove imaging using LMMSE-based filter. The wavelet dependent is the resulting from determining the performance of interscale LMMSE. In the MATLAB software, the capability of multiscale LMMSE-based filter will be investigated as conjunction of reducing speckle noise resulting from the ultrasound images back from the scattered wave. This filter also will be test on its performance and will be compared with other conventional filters such as Lee and Median filter.

As the LMMSE filter was developed in the framework of additive white noise, applying to speckle noise would require ultrasound imaging to work in homomorphic framework. This is because the speckle effect in ultrasound images is a type of multiplicative noise so by applying the logarithm equation, the make-up noise will be transforming into additional noise.

The variance for noise will be set accordingly from 0.1 to 2.0 with 0.1 increment. For each loop, 100 times of experiment will be done to achieve high acquisition of data result for PSNR and SSIM. By using this result, the real image of ultrasound will also be analysed. This method also will be applied to the other filter proposed in order to stimulate the comparison. Such as in Lee filter there will be 3X3, 5X5 and 7X7 matrices so altogether will be running 100 times for its PSNR and SSIM. The result of these 3 filter will be analysed to form further enhanced experimenting.

3.1.1 Flow chart



3.2 Gantt Charts

3.2.1 Final Year Project 1

Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Selection of the project														
topic														
Preliminary research														
work														
Preliminary report														
submission														
Experiment Research														
Submission of Interim draft report												•		
Submission of Interim Report													۲	

Figure 3: The Gantt Chart For FYP1.

3.2.2 Final Year Project 2

No	Task	week													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.	Project function design using MATLAB														
2.	SSIM Test – Run for different wavelet and images														
3.	PSNR Running & Testing														
4.	Run MLMMSE with ultrasound image														
5.	PosterPresentation(Electrex)														
6.	Submission of Progress report														
7.	Submission of Technical report														
8.	Oral presentation (VIVA)														
9.	Submission of project dissertation														

Figure 4: The Gantt Chart for FYP2

CHAPTER 4 RESULT AND DISCUSSION

4.1 Simulated Images

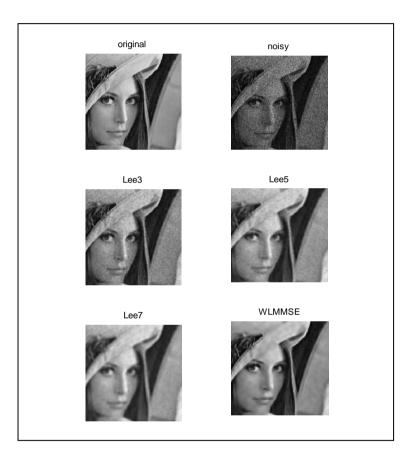


Figure 5 : Processed image with different filter

By running the code in the MATLAB software the result came out as in figure 5 where the image result using MLMMSE wavelet is the most similar to the original image. The image with additive noise named 'noisy' above is totally blur with a lot of ringing effect. The image resulting from using Lee 7x7 is better than Lee 3x3 and Lee 5x5 but still the MLMMSE image is the better one. All this filter approach is purposing in smoothing the homogeneous of the images but narrowly to compare the MLMMSE with others. The speckle in original images is a multiplicative noise where the noise is in static independent. In this experiment we vary the variance since the variance means its sample pixels are equivalent to the pixel of the original images.

Lee 3x3 images is clear but with a lot of dots of scattered pixel. Lee 3x3 resulting in high number of PSNR but very low in SSIM. Compared to Lee 5x5 all the scattered pixel is reduce resulting in slightly high value of SSIM but the PSNR value is lower than the Lee 3x3. In Lee 7x7 resulting image, the pixel is in better arrangement resulting smoother image but still the blur effect covered it after all. When it comes to MLMMSE filter resulting image, we can see it clearly that the image is in good arrangement of pixel without blurry effect.

The MLMMSE resulting in good images due to its interscale system being able to extract the signal from noisy image. It's also have good cooperation with the coefficient of wavelet and Gaussian application. The MLMMSE filter will optimize its feature with the Gaussian as its signal below distribution. The results of the MLMMSE filter compared to Lee 3x3, Lee 5x5, and Lee 7x7 with varying number of variance is tabulated in the table below:

4.2 Tabulated data

v_n^2	0.1	0.2	0.3	0.4	0.5
	SSIM	SSIM	SSIM	SSIM	SSIM
NOISY	0.39	0.29	0.24	0.20	0.18
LEE 3X3	0.71	0.60	0.54	0.50	0.46
LEE 5X5	0.76	0.70	0.66	0.63	0.60
LEE 7X7	0.74	0.71	0.69	0.67	0.65
WLMMSE	0.83	0.76	0.73	0.70	0.69

Table 1: SSIM data from different filter with variance 0.1-0.5

v_n^2	0.6	0.7	0.8	0.9	1.0
	SSIM	SSIM	SSIM	SSIM	SSIM
NOISY	0.16	0.14	0.13	0.12	0.11
LEE 3X3	0.43	0.41	0.39	0.37	0.36
LEE 5X5	0.57	0.56	0.53	0.52	0.50
LEE 7X7	0.63	0.62	0.60	0.59	0.58
WLMMSE	0.68	0.68	0.67	0.66	0.66

Table 2 : SSIM data from different filter with variance 0.6-1.0

v_n^2	1.1	1.2	1.3	1.4	1.5
	SSIM	SSIM	SSIM	SSIM	SSIM
NOISY	0.10	0.10	0.09	0.09	0.08
LEE 3X3	0.34	0.33	0.32	0.31	0.30
LEE 5X5	0.49	0.48	0.46	0.45	0.44
LEE 7X7	0.57	0.56	0.55	0.54	0.53
WLMMSE	0.65	0.65	0.64	0.64	0.63

Table 3: SSIM data from different filter with variance 1.1-1.5

v_n^2	1.6	1.7	1.8	1.9	2.0
	SSIM	SSIM	SSIM	SSIM	SSIM
NOISY	0.08	0.08	0.07	0.07	0.07
LEE 3X3	0.29	0.28	0.27	0.27	0.26
LEE 5X5	0.43	0.42	0.41	0.41	0.40
LEE 7X7	0.52	0.51	0.50	0.50	0.49
WLMMSE	0.63	0.62	0.61	0.61	0.60

Table 4: SSIM data from different filter with variance 1.6-2.0

As we can see from the Table 1 to Table 4 the additive noise image have the lower value of PSNR and SSIM in all variance varying number which show the image is in bad condition. While using MLMMSE the PSNR and SSIM value is a little bit higher than other filter which indicating a good result. But when the value of the variance increase, the PSNR value for MLMMSE decrease due to instability from the filter coefficient. In contrast, the SSIM for MLMMSE filter still show the most stable compared to other 3 filters even though the variance had been increased to 2.0.

4.3 Graphs

4.3.1 PSNR versus Variance

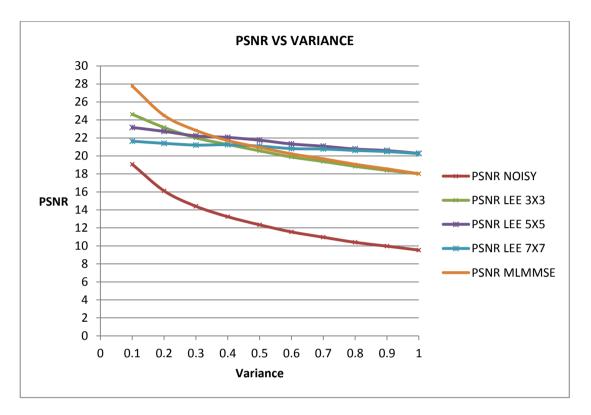


Figure 6 : PSNR versus Variance

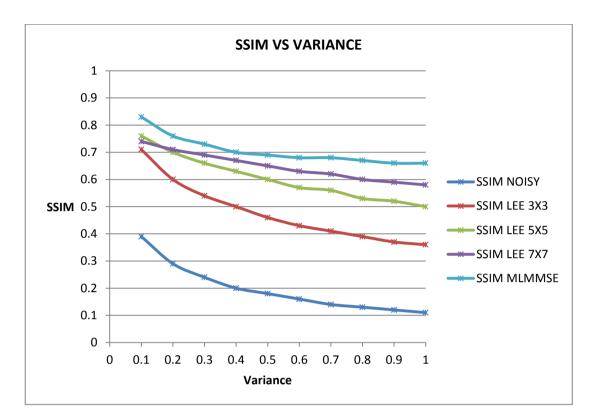


Figure 7 : SSIM versus Varience

Figure 6 shows the graph of PSNR with variance had been plotted from the resulting table. From the Figure 6 it can be said that the MLMMSE filter will be in its best performance when the variance value is low. As the variance increased, the PSNR for MLMMSE decreased drastically which show unhealthy performance compared to Lee 3x3 and Lee 5x5. This indicate that the maximum power of MLMMSE filter decrease with increasing variance and its power of corrupting noise also decrease.

Figure 7 shows the graph of SSIM with variance had been plotted accordingly from the simulated data. In this graph, the MLMMSE filter showed the most stable SSIM when the value of variance increased from 0.1 to 2. The structural similarity for MLMMSE filter going stable from 0.83 for 0.1 variance until 0.60 for 2.0 variance. Compared to other filter, SSIM for Lee 3x3 filter show the most unstable or weak in conducting uncompressed or distortion-free image as a sample or reference.

4.4 PSNR data.

4.4.1 Lena image

	PSNR WAVELET							
v_n^2	BIOR 1.1	BIOR 1.3	BIOR 2.2	BIOR 2.4	BIOR 3.3	DB 2	DB 3	DB 4
0.1	27.7847	27.7893	27.8242	27.8364	27.8152	27.7819	27.7940	27.8387
0.2	24.5350	24.5912	24.4933	24.5281	24.5503	24.5200	24.5674	24.5244
0.3	22.8170	22.8437	22.8105	22.8448	22.8104	22.8204	22.7828	22.8047
0.4	21.7056	21.7108	21.6984	21.7367	21.7278	21.7319	21.7083	21.7206
0.5	21.0087	21.7012	20.9461	20.1269	20.9417	20.9365	20.9584	20.8809
0.6	20.2629	20.2791	20.2796	20.2751	20.2915	202561	20.2710	20.2835
0.7	19.6746	19.6858	19.6369	19.6641	19.6643	19.7297	19.7094	19.7042
0.8	19.0713	19.0773	19.0895	19.1275	19.0898	19.0615	19.0676	19.1110
0.9	18.5311	18.5617	18.5515	18.5497	18.5237	18.4984	18.5365	18.5117
1.0	17.9317	18.0231	18.0183	18.0179	17.9757	18.0176	17.9630	18.0024

Table 5: PSNR wavelet for LENA.jpg image

4.4.2 Barbara image

	PSNR WAVELET							
v_n^2	BIOR 1.1	BIOR 1.3	BIOR 2.2	BIOR 2.4	BIOR 3.3	DB 2	DB 3	DB 4
0.1	23.4616	23.4726	23.5130	23.5241	23.5616	23.5834	23.5967	23.6025
0.2	20.1658	20.1630	20.1802	20.1936	20.1986	20.2007	20.2109	20.2197
0.3	19.1335	19.1398	19.1331	19.1403	19.1509	19.1953	19.1959	19.2065
0.4	18.5417	18.5392	18.5685	18.5699	18.6678	18.6784	18.6755	18.6953
0.5	18.1421	18.1415	181407	18.1501	18.1706	18.1906	18.2010	18.2114
0.6	17.7317	17.7520	17.7508	17.7564	17.7627	17.7967	17.7997	17.8065
0.7	17.3259	17.3247	17.3240	17.3295	17.3489	17.3985	17.3989	17.4257
0.8	16.9796	16.9518	16.9515	16.9516	16.9983	17.0019	17.1254	17.2568
0.9	16.5935	16.5201	16.5213	16.5277	16.5371	16.5974	16.6723	16.6865
1.0	16.2488	15.7546	15.7541	15.7549	15.7662	15.7937	15.8012	15.8214

Table 6: PSNR wavelet for BARBARA.jpg image

4.4.3 Boat image

	PSNR WAVELET							
v_n^2	BIOR 1.1	BIOR 1.3	BIOR 2.2	BIOR 2.4	BIOR 3.3	DB 2	DB 3	DB 4
0.1	23.5090	23.5119	23.5496	23.5234	23.4902	23.4899	23.4894	23.4801
0.2	22.4590	22.4797	22.4817	22.5108	22.4924	22.4785	22.4685	22.4661
0.3	21.0047	21.1057	21.2478	21.3107	21.2987	21.2754	21.2517	21.2239
0.4	20.0666	20.1571	20.1975	20.2007	20.1999	20.1742	20.1685	20.1621
0.5	19.4185	19.4197	19.4521	19.4687	19.4421	19.4321	19.4211	19.4100
0.6	18.8157	18.8192	18.8214	18.8294	18.8241	18.8136	18.8107	18.0967
0.7	18.2939	18.2993	18.3025	18.3111	18.3101	18.3097	18.3087	18.3054
0.8	17.8343	17.8381	17.8425	17.8473	17.8215	17.8157	17.8099	17.8082
0.9	17.8274	17.8376	17.8397	17.8124	17.8001	17.7985	17.7635	17.7621
1.0	17.3721	17.3797	17.4527	17.4687	17.4527	17.4437	17.4421	17.4397

Table 7: PSNR wavelet for BOAT.jpg image

In the tables above is the result for PSNR for different images where different wavelet is being used. The wavelet use for this experiment is Bior 1.1, Bior 1.3, Bior 2.2, Bior 2.4, Bior 3.3, DB 2, DB 3 and DB 4. The most stable wavelet will be selected to run with ultrasound image. This wavelet is the section maps in the image of the continuous variable derive with the sequence of coefficient. It is resulting of resembling the original image function. It works as when the higher or greater detail are sum together it will help to precisely increase the approximation of the function. As we can see from all table the PSNR value will increase from Bior 1.1 untill Bior 2.4. Starting from Bior 3.3 the value is decreasing until the last wavelet which is DB 4. This result shows that Bior 2.4 can be selected as the best wavelet to run with the ultrasound images. This wavelet is a continuous wavelet which its changes the continuous function to a very high redundant function where it interpret in two way of scale and translation.

4.5 MLMMSE Filter With 'DB2' Wavelet For "LENA.JPG" Image

Variance; $v_n^2 = 0.02$					
Wavelet	db2				
Min	Max				
28.6905	34.4336				
28.6704	34.4013				
28.7254	34.4839				
28.6742	34.4177				
28.6518	34.3689				
28.6768	34.4122				
28.6725	34.4057				
28.6803	34.4089				
28.6651	34.3825				
28.6708	34.4054				

Table 8 : db2 with 0.02 variance

Variance; $v_n^2 = 0.04$				
Wavelet	db2			
Min	Max			
25.6621	34.3000			
25.6311	34.2991			
25.6441	34.3546			
25.6391	34.3065			
25.6892	34.3673			
25.6619	34.3546			
25.6531	34.3366			
25.6517	34.3094			
25.6659	34.3112			
25.6596	34.3176			

Table 9 : db2 with 0.04 variance

Variance;	Variance; $v_n^2 = 0.06$				
Wavelet	db2				
Min	Max				
23.8740	33.0919				
23.9298	33.1105				
23.9124	33.0943				
23.8854	33.0031				
23.8752	32.9952				
23.9130	33.0678				
23.8667	33.0754				
23.9049	33.0922				
23.9159	33.0419				
23.8778	32.9915				

Table 10 : db2 with 0.06 variance

Variance; $v_n^2 = 0.02$				
Wavelet	db3			
Min	Max			
28.6631	34.5428			
28.6620	34.5408			
28.6731	34.5661			
28.6695	34.5366			
28.6462	34.4899			
28.6523	34.5187			
28.6647	34.5261			
28.6415	34.4876			
28.6579	34.5291			
28.6479	34.5069			

Variance; $v_n^2 = 0.04$				
Wavelet	db3			
Min	Max			
25.6643	34.3498			
25.6737	34.4003			
25.6665	34.3755			
25.6585	34.3664			
25.6511	34.4153			
25.6546	34.4132			
25.6721	34.4167			
25.6587	34.3945			
25.6658	34.3439			
25.6580	34.4087			

Table 11 : db3 with 0.02 varianceTable 12 : db3 with 0.04 variance

Variance; $v_n^2 = 0.06$				
Wavelet	db3			
Min	Max			
23.8950	33.0567			
23.8819	33.0812			
23.9139	33.1066			
23.8697	33.0667			
23.8802	33.0355			
23.9021	33.0845			
23.8852	33.0210			
23.9011	33.0156			
23.8991	33.0786			
23.8869	33.0707			

Table 13 : db3 with 0.06 variance

Variance; $v_n^2 = 0.02$	
Wavelet	db4
Min	Max
28.6598	34.4850
28.6684	34.5001
28.6711	34.5036
28.6736	34.5380
28.6596	34.4751
28.6655	34.5331
28.6762	34.5212
28.6784	34.5235
28.6742	34.5281
28.6578	34.5127

Table 14 : db4 with 0.02 variance

Variance; $v_n^2 = 0.04$	
Wavelet	db4
Min	Max
25.6326	34.2716
25.6474	34.2592
25.6191	34.2794
25.6508	34.2999
25.6507	34.3215
25.6810	34.3581
25.6474	34.2788
25.6362	34.2490
25.6401	34.3268
25.6629	34.2920

Table 15 : db4 with 0.04 variance

r	
Variance; $v_n^2 = 0.06$	
Wavelet	db4
Min	Max
23.8850	33.0275
23.8854	33.0192
23.9044	32.9942
23.8787	33.0115
23.8844	32.9563
23.8967	32.9513
23.8939	33.0318
23.8894	32.9670
23.9073	32.9968
23.8603	32.9664

Table 16 : db4 with 0.06 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior1.3
Min	Max
28.6379	34.1452
28.6758	34.1870
28.6633	34.1752
28.6599	34.1685
28.6947	34.2172
28.6663	34.1892
28.6749	34.1988
28.6592	34.1724
28.6514	34.1567
28.6823	34.1859

Table 17 : bior 1.3 with 0.02 variance

Variance; $v_n^2 = 0.04$	
Wavelet	bior1.3
Min	Max
25.6582	34.3914
25.6468	34.4510
25.6468	34.3970
25.6634	34.4166
25.6707	34.3850
25.6719	34.4055
25.6675	34.4008
25.6508	34.3685
25.6533	34.3757
25.6400	34.3820

Table 18 : bior 1.3 with 0.04 variance

Variance; $v_n^2 = 0.06$	
Wavelet	bior 1.3
Min	Max
23.8705	33.4159
23.9058	33.3789
23.8793	33.4110
23.8830	33.3698
23.9043	33.4062
23.8900	33.4044
23.9003	33.4387
23.9192	33.4115
23.8761	33.3849
23.8797	33.4444

Table 19 : bior 1.3 with 0.06 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior 2.2
Min	Max
28.6667	34.2096
28.6683	34.2155
28.6724	34.2265
28.6462	34.1723
28.6784	34.2410
28.6662	34.2205
28.6586	34.1983
28.6682	34.2062
28.6589	34.2024
28.6537	34.1873

Table 20 : bior 2.2 with 0.02 variance

Variance; $v_n^2 = 0.04$	
Wavelet	bior 2.2
Min	Max
25.6574	34.1196
25.6565	34.1133
25.6552	34.1155
25.6716	34.1250
25.6583	34.1160
25.6657	34.1034
25.6435	34.1146
25.6455	34.0722
25.6560	34.0920
25.6618	34.0636

Table 21 : bior 2.2 with 0.04 variance

Variance; $v_n^2 = 0.06$	
Wavelet	bior 2.2
Min	Max
23.8992	33.3485
23.9123	33.3866
23.8638	33.3217
23.8969	33.4069
23.9099	33.3694
23.8740	33.3717
23.8936	33.3564
23.8949	33.3611
23.8701	33.3400
23.8899	33.3929

Table 22 : bior 2.2 with 0.06 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior 2.4
Min	Max
28.6710	34.1985
28.6730	34.2193
28.6331	34.1554
28.6526	34.2087
28.6558	34.2000
28.6610	34.1988
28.6785	34.2083
28.6551	34.2137
28.6496	34.1974
28.6545	34.1907

Table 23 : bior 2.4 with 0.02 variance

Variance; $v_n^2 = 0.04$	
Wavelet	bior 2.4
Min	Max
25.6638	34.0752
25.6652	34.0513
25.6782	34.0859
25.6571	34.0296
25.6440	34.0927
25.6592	34.0992
25.6718	34.0502
25.6324	34.0232
25.6608	34.0515
25.6582	34.0475

Table 24 : bior 2.4 with 0.04 variance

Variance; $v_n^2 = 0.06$	
Wavelet	bior 2.4
Min	Max
23.8986	33.2904
23.8978	33.3005
23.8869	33.2828
23.8926	33.2950
23.9026	33.3016
23.8964	33.2570
23.9214	33.3245
23.9441	33.3016
23.9317	33.2811
23.9005	33.3301

Table 25 : bior 2.4 with 0.06 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior 3.3
Min	Max
28.6799	33.0323
28.6482	32.9808
28.6575	32.9828
28.6470	32.9447
28.6555	32.9873
28.6862	33.0174
28.6826	33.0377
28.6514	32.9809
28.6632	32.9972
28.6579	32.9872

Table 26 : bior 3.3 with 0.02 variance

Variance; $v_n^2 = 0.04$	
Wavelet	bior 3.3
Min	Max
25.6491	32.2904
25.6583	32.2952
25.6355	32.2667
25.6544	32.2818
25.6523	32.2924
25.6605	32.2630
25.6346	32.2581
25.6630	32.3095
25.6605	32.2777
25.6611	32.3134

Table 27 : bior 3.3 with 0.04 variance

Variance; $v_n^2 = 0.06$	
Wavelet	bior 3.3
Min	Max
23.9117	31.7869
23.8938	31.7046
23.8977	31.7106
23.9059	31.7713
23.9219	31.8161
23.8990	31.7643
23.9155	31.7700
23.8745	31.7465
23.8991	31.7439
23.8878	31.7187

Table 28 : bior 3.3 with 0.06 variance

4.6 MLMMSE Filter With Different Wavelet For "BARBARA.jpg" Image.

Variance; $v_n^2 = 0.02$	
Wavelet	db2
Min	Max
28.9104	32.5985
28.9068	32.6021
28.9024	32.6158
28.8666	32.5708
28.9345	32.6392
28.8914	32.6080
28.9127	32.6258
28.9095	32.6179
28.8925	32.5843
28.8733	32.5725

Table 29 : db2 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	db3
Min	Max
28.9389	32.9288
28.9191	32.9030
28.9029	32.8769
28.9128	32.8782
28.9104	32.8754
28.8901	32.8467
28.9148	32.8989
28.8997	32.8843
28.8825	32.8687
28.8882	32.8318

Table 30 : db3 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	db4
Min	Max
28.9025	32.9427
28.8959	32.9414
28.9133	32.9594
28.8583	32.9042
28.9193	32.9667
28.8926	32.9271
28.8901	32.9377
28.8796	32.9223
28.8928	32.9267
28.9007	32.9438

Table 31 : db4 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior1.3
Min	Max
28.8945	32.5237
28.9006	32.5469
28.9064	32.5372
28.9185	32.5556
28.9030	32.5468
28.8744	32.5155
28.8800	32.5188
28.8894	32.5280
28.8964	32.5438
28.8867	32.5156

Table 32 : bior 1.3 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior2.2
Min	Max
28.9040	32.7512
28.8674	32.7112
28.9188	32.8125
28.8742	32.7330
28.8958	32.7637
28.8966	32.7530
28.8958	32.7567
28.8727	32.7476
28.8676	32.7222
28.8909	32.7713

Table 33 : bior 2.2 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior2.4
Min	Max
28.9017	32.7698
28.9006	32.7644
28.9225	32.7972
28.8742	32.7438
28.9103	32.8035
28.9018	32.7725
28.8865	32.7399
28.9052	32.7693
28.9190	32.7852
28.8914	32.7761

Table 34 : bior 2.4 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior3.3
Min	Max
28.8827	32.1452
28.9183	32.1873
28.9225	32.1864
28.8809	32.1278
28.9075	32.1579
28.9010	32.1502
28.8974	32.1561
28.8704	32.1045
28.8844	32.1245
28.9192	32.1881

Table 35 : bior 3.3 with 0.02 variance

4.7 MLMMSE Filter With Different Wavelet For "BOAT.jpg" Image.

Variance; $v_n^2 = 0.02$	
Wavelet	db2
Min	Max
28.3395	32.5980
28.3464	32.6183
28.3446	32.6225
28.3683	32.6361
28.3594	32.6326
28.3575	32.6239
28.3127	32.5761
28.3207	32.5957
28.3451	32.6225
28.3582	32.6460

Variance; $v_n^2 = 0.02$ Wavelet db3 Min Max 28.3718 32.7229 28.3515 32.6951 28.3577 32.7002 32.7207 28.3591 28.3409 32.6902 28.3587 32.7016 28.3443 32.6802 28.3578 32.7096 28.3672 32.7202 28.3381 32.6667

Table 36 : db2 with 0.02 variance

Table 37 : db3 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	db4
Min	Max
28.3588	32.6890
28.3417	32.6664
28.3497	32.6764
28.3616	32.6846
28.3522	32.6745
28.3833	32.7146
28.3600	32.6739
28.3441	32.6601
28.3527	32.6578
28.3419	32.6572

Table 38 : db4 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior2.2
Min	Max
28.3573	32.6575
28.3552	32.6498
28.3879	32.6784
28.3347	32.6154
28.3370	32.6198
28.3857	32.6601
28.3361	32.6235
28.3643	32.6424
28.3679	32.6501
28.3588	32.6405

Table 39 : bior 2.2 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior1.3
Min	Max
28.3535	32.5762
28.3342	32.5677
28.3659	32.6093
28.3587	32.6039
28.3735	32.6260
28.3508	32.5793
28.3326	32.5602
28.3420	32.5575
28.3397	32.5738
28.3660	32.5998

Table 40 : bior 1.3 with 0.02 variance

Variance; v	Variance; $v_n^2 = 0.02$	
Wavelet	bior2.4	
Min	Max	
28.3586	32.6305	
28.3469	32.5868	
28.3619	32.6210	
28.3626	32.6288	
28.3508	32.6107	
28.3774	32.6395	
28.3658	32.6312	
28.3503	32.6015	
28.3209	32.5616	
28.3424	32.5856	

Table 41 : bior 2.4 with 0.02 variance

Variance; $v_n^2 = 0.02$	
Wavelet	bior3.3
Min	Max
28.3575	31.8527
28.3578	31.8439
28.3466	31.8442
28.3557	31.8746
28.3623	31.8692
28.3610	31.8726
28.3556	31.8641
28.3455	31.8558
28.3553	31.8516
28.3512	31.8462

Table 42 : bior 3.3 with 0.02 variance

The table above is the result for MLMMSE filter run with different wavelet and different images to obtain SSIM value. The wavelet used for this experiment is db 2, db 3, db 4, bior 1.3, bior 2.2, bior 2.4, and bior 3.3. Different wavelet being use to view the most dependent wavelet in order to proceed with ultrasound image testing. Together with that the different images also being use to find the stability value in different wavelet. Based on the result table, it is found that the wavelet bior 2.4 is the most stable wavelet for LMMSE filter. The value for bior 2.4 is steadily greater than other image. The SSIM value for this wavelet is always better than other comparing wavelet. The SSIM is an index value for the picture where it can view the user to compare the quality of the image. It helps for assessing the conceptual image and to calculate the quantity of the visible error in the image. Normally the two different image will be used in assessing for example the distorted image and one other sample image using the different properties of the images. For this case of Lena image we use the different variance with different wavelet and obtain the result. For the rest of images which is Barbara and Boat we only vary the wavelet and keep the same variance. The variance for Lena images we used 3 different values which is 0.02, 0.04, and 0.06. But for Barbara and Boat images we keep the variance to 0.2 .Even though Barbara and Boat did not use the different variance, the result still side on this one wavelet which is bior 2.4.

4.8 Performance Comparison For Different Images

4.8.1 Lena.png Image

Images 'LENA.PNG'	SSIM INDEX
Noisy	9.97594455594804
Lee 3X3	18.4654581486020
Lee 5X5	20.6971380122139
Lee 7X7	20.6397218291140
MLMMSE	20.9616971853896

Table 43 : SSIM value using different filter on LENA.png image

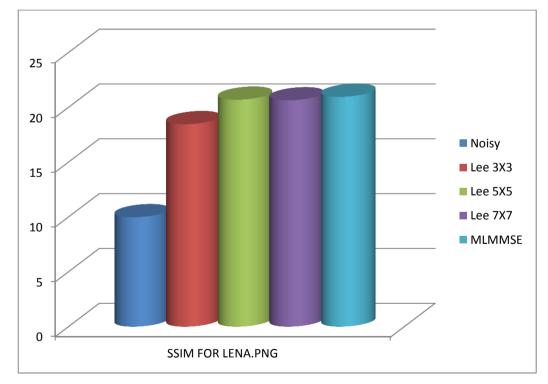


Figure 8 : SSIM for Lena.png image

4.8.2 Barbara.png Image

Images 'BARBARA.PNG'	SSIM INDEX
Noisy	9.95689400662468
Lee 3X3	17.2837982985909
Lee 5X5	18.1616980707699
Lee 7X7	18.3416319874111
MLMMSE	18.8853243243270

Table 44 : SSIM value using different filter on BARBARA.png image

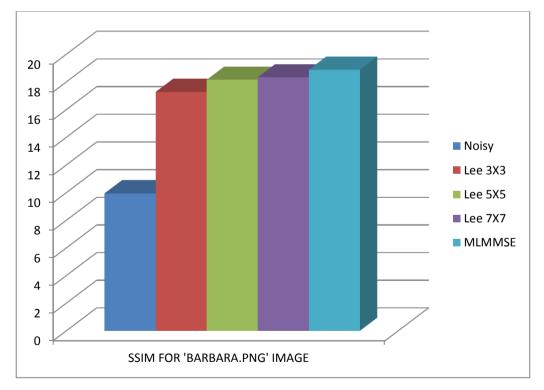


Figure 9 : SSIM for Barbara.png image

4.8.3 Boat.png Image

Images 'BOAT.PNG'	SSIM INDEX
Noisy	9.96355545153078
Lee 3X3	18.1340937834487
Lee 5X5	19.7427587445986
Lee 7X7	19.4859374190653
MLMMSE	20.0990227855539

Table 45 : SSIM value using different filter on LENA.png image

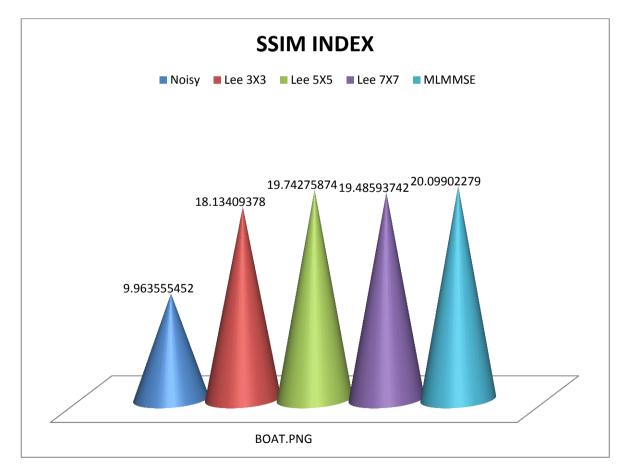


Figure 10 : SSIM for Boat.png image

4.9 MLMMSE using ultrasound images.

4.9.1 ENL value for simulated image = 9.0863; 9.1255

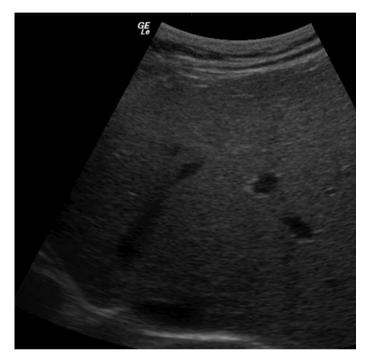


Figure 11 : Liver.png overall noisy image

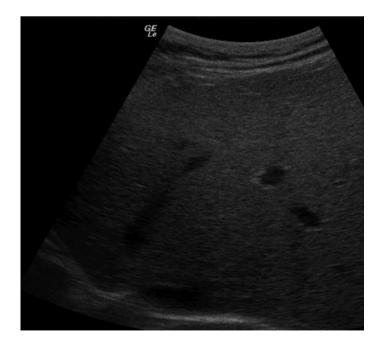


Figure 12 : Liver.png overall denoised image

4.9.2 ENL value for simulated image = 32.7211; 33.2272

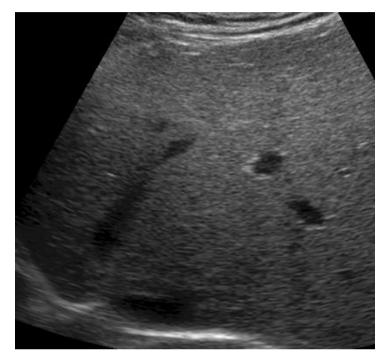


Figure 13 : Liver.png with selected homogenous noisy image

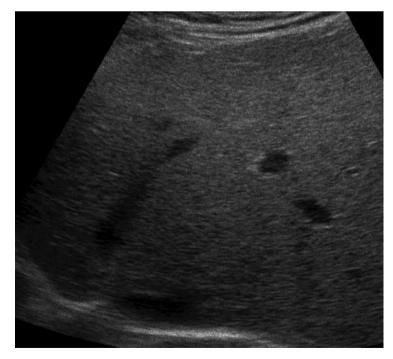


Figure 14:Liver.png with selected homogenous denoised image

4.9.3 ENL value for simulated image = 6.5746; 6.5787



Figure 15 : Fetal.png overall noisy image



Figure 16 : Fetal.png overall denoised image

4.9.4 ENL value for simulated image = 13.7483; 13.7581



Figure 17 : Fetal.png with selected homogenous noisy image



Figure 18 : Fetal.png with selected homogenous denoised image

Figure 11 - 18 shows the simulated ultrasound images using bior 2.4 wavelet. The entire image is compared from its original image which is states as 'noisy image' in the above result. The image is divided into two that is noisy and denoised. From that it is break down again into two parts for which first part is running for overall image and the second one is downscale to some certain homogenous part of the picture. Figure 11 - 14 is the ultrasound image for liver and for Figure 15 - 18 is the image of fetal during 7 months pregnancy.

In this stage the equivalent number of looks (ENL) is analysed from the image. The ENL is an important measurement in the modeling image. It is normally known as statistical modeling of the multilook ultrasound images. ENL estimation is calculated by discovering at some part of the moment image of multilook data. The data will be assessing the covariance is scattered in image distribution. In the early part, the second order level of the image moment will provide an extension called polarimetric and it is originated from the ENL definition. This will also provide the matric variate moment from the ENL estimator. After that, the rest estimator will be getting from the log-independent matrix moment of the images. The ENL is known to be less in affected from the texture. Because of that the ENL gives better results comparing to other estimator such as Gaussian statistic in the complex of scattering the coefficient and other. ENL also estimate the empirical density for the whole image and it also can be selected manually to calculate over region of interest. For the Liver.png above, the ENL value is 9.125 for the overall image and after the homogenous regions were selected the ENL value gives 33.22. Same goes with the fetal image where overall ENL is 6.57 and for homogeneous region is 13.75. This indicates that the MLMMSE filter can obtain better ENL value above homogenous region. Compared the figure of liver and fetal, the liver's ENL value is 3 to 4 times improvement if being compared to the noisy image which show a little dependency for this image. The fetal image is up to 2 times better if be compared with the noisy image over the homogenous selected region and this show a lot of redundancy in the image or a lot of unscattered signal in the images where it need more smoothest selected region to get the best ENL value for the images. In addition, we can also presume that the speckle noise is fully developed in this image and multiplicative model is in perfect performance. This MLMMSE filter demonstrates a lot dependency of ultrasound image can be achieved whether in the homomorphic selected region or even for overall ultrasound image.

CHAPTER 5 CONCLUSION

In conclusion, the MLMMSE shows the most dependent filter as compared to Lee 3X3, Lee 5X5, and Lee 7X7 as they through the experiment with increasing value of variance. PSNR for MLMMSE filter is at optimum when the variance value is small but decrease with high variance. This indicates that the quality to reconstruction image of loss compression for MLMMSE filter is low. Even though the high value of PNSR normally approve the quality, in some cases it may not where the image should exclusively be compared from the same nature of image such as pixel or codec on image compression. For structural similarity index, SSIM, it is incomparable that the MLMMSE filters achieve great result where the value of SSIM for this filter is above other filter at all time at any variance value. This shows that initial uncompressed or distortion for this MLMMSE filter is at best when comparing to other filter in this experiment. In next research the other filter such as Median, Frost, Mean or map will be analyzed to compare with MLMMSE filter in achieving precisely order of result for clearer prove. For the ultrasound images the ENL value obtain for all test images resulting in better quality after run with MLMMSE filter. This indicates that the MLMMSE filter can obtain better ENL value above homogenous region and also for overall image. In addition, we can also presume that the speckle noise is fully develop in this image and multiplicative model is in perfect performance. This MLMMSE filter demonstrates a lot dependency of ultrasound image can be achieved whether in the homomorphic selected region or even for overall ultrasound image.

CHAPTER 6 REFERENCES

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APPENDICES

APPENDIX A

EXPERIMENTAL ORIGINAL IMAGES



LENA.jpg



BOAT.jpg



BARBARA.jpg

APPENDIX B

MATLAB SOURCE CODE

%L. Zhang et al, "Multiscle LMMSE-based image denoising with optimal wavelet selection," %IEEE Trans. on Circuits and Systems for Video Technology, vol. 15, pp. 469-481, April 2005. %Note: %1. You need Matlab Wavelet Toolbox to run the code. %2. In this code, we suppose the input image is a nxn square matrix (just for some convenience:). You may easily revise the code for non-square nxm images. clear;clc;close all ima=imread('lena.tif','tif'); n=length(ima);%% We suppose ima is a nxn square image. You may easily revise the code for nxm images. ima=double(ima); v=25; noi=v*randn(n,n); iman=ima+noi; figure(1);clf; imshow(iman, [0 255]); pima=mean(mean(ima.^2)); $snro=10*log10(pima/(v^2))$ ୫୫୫୫୫୫୫୫୫୫୫୫୫୫୫୫୫୫୫ [ld,hd,lr,hr]=wfilters('bior1.3'); wbase=2; %%%%wbase: %1-bior1.1; 2-bior1.3; 3-bior2.2; 4-bior2.4 %5-bior3.3; 6-db2; 7-db3; 8-db4 J=3; [S,HW,WH,WW,etl] = ocwt2d(iman,ld,hd,J); $s = [4 \ 6 \ 8 \ 10];$ rWW=denss(WW,v,wbase,1,s); rWH=denss(WH,v,wbase,2,s); rHW=denss(HW,v,wbase,3,s); rima=iocwt2d(S,rHW,rWH,rWW,etl,lr,hr); err=ima-rima; perr=mean(mean(err.^2)); snrss=10*log10(pima/perr) figure(2);clf; imshow(rima, [0 255]);