CHAPTER 6

FUSION BASED WAVELET FILTER (FBWF)

6.1 BACKGROUND

Chapter 4 and 5 focused on two new wavelet based denoising algorithms of which one modifies the coefficients above threshold and the other below the threshold.

- The improved adaptive threshold function based filter, SIIAWF reduced the fixed bias of the soft thresholding and reduced the number of zero coefficients for a range of thresholds defined. The preliminary coefficient clustering, weighted variance estimate based subband adaptive threshold selection along with the new and improved adaptive threshold function increased the PSNR as well as EPI values.
- The second algorithm, ISTWF, operated on coefficients below threshold, produced a comparatively better improvement in PSNR and with good EPI. This is achieved by modifying the impulsive nature of soft thresholding function.
- Combining the outputs of the above two schemes, through a fusion approach, further enhancement in the filter performance is achieved.

This chapter describes a new fusion scheme to enhance the US image quality, by combining the output of the above two thresholding algorithms with a new fusion rule.

6.2 IMAGE FUSION

Image fusion is a procedure in which a number of source images are integrated together to get a resultant image which has better information content than the individual source images. As this technique can be applied for different real life applications, it has gained maximum popularity in recent image processing research. The various application areas of fusion are in remote sensing, medical diagnosis and target recognition. Rahman et al (2010) emphasized that developing an efficient fusion technique for imaging applications would become essential, for getting a more informative image, from a number of source images captured through different sensors or imaging systems. Since the presence of noise has become a common phenomenon of practical imaging systems, a combined approach involving image fusion and noise suppression is indispensable to improve the image quality.

Various approaches have been developed for image fusion in the past two decades. The information from different source images is combined at various stages to get a fused output. Based on this, different types of fusion algorithms are developed, namely pixel-level, feature-level, and decision-level fusion techniques. The pixel-level fusion integrates the raw source images to get a more informative output image. The merit of pixel level fusion is that it can preserve original information better than feature or decision-level fusion approaches. Feature-level fusion is carried out using various features of images like edges or regions and this type of methods is robust to noise. In decision level fusion technique, image descriptions are integrated directly, for example, in the form of relational graphs (Yang & Li 2012).

The objective of pixel-level image fusion is to obtain an informative fused image, by combining visual information content of different source images, without any distortion or loss of information. Among various image fusion techniques developed earlier in the literature like those of Yang & Li

(2012), Rahman et al (2010) and Yong et al (2010) multi-scale transform based methods are the most successful. The steps of operation of multiscale transforms based image fusion are: (i) decomposition of the source images using multiscale transformations, into various resolutions and orientations. (ii) applying fusion rules to integrate the multi-scale representations (iii) constructing the fused image from the combined multi-scale coefficients by applying inverse transform. DWT based fusion scheme for noise removal must involve a suitable algorithm to suppress noise from the wavelet coefficients. The denoised coefficients are combined using an appropriate fusion rule to get the fused output.

6.2.1 Fusion Based Denoising

In recent years, image fusion has found its applications in various areas. In real world scenarios, it is assumed that the multiple source images of an image fusion process contain only relevant information to produce the required output. But this does not hold true more often than not. Thus, image fusion problem needs to be addressed from a more complex, fusion-denoising point of view, in order to provide a fused result of greater quality. The basic principle underlying any fusion based algorithm is as follows: Two input images are taken as source images. They are decomposed using wavelet transform. An activity measure is calculated for each of the detail subbands. Based on a decision rule, fusion is then carried out. The used coefficients are then reconstructed using inverse wavelet transform.

This chapter discusses a new fusion based despeckling algorithm with improved edge preservation. The two denoised outputs, one from the SIIAWF and the other from ISTWF are taken as the source images. In the first level, an inter scale dependency based entropy fusion is performed to enhance the denoised outputs. At the second level, a weighted entropy based fusion is applied between the two enhanced denoised outputs to obtain a single fused output. The detailed explanation of the proposed fusion based enhancement algorithm is explained below.

6.2.2 Block Diagram of the Proposed Fusion Based Wavelet Filter (FBWF)

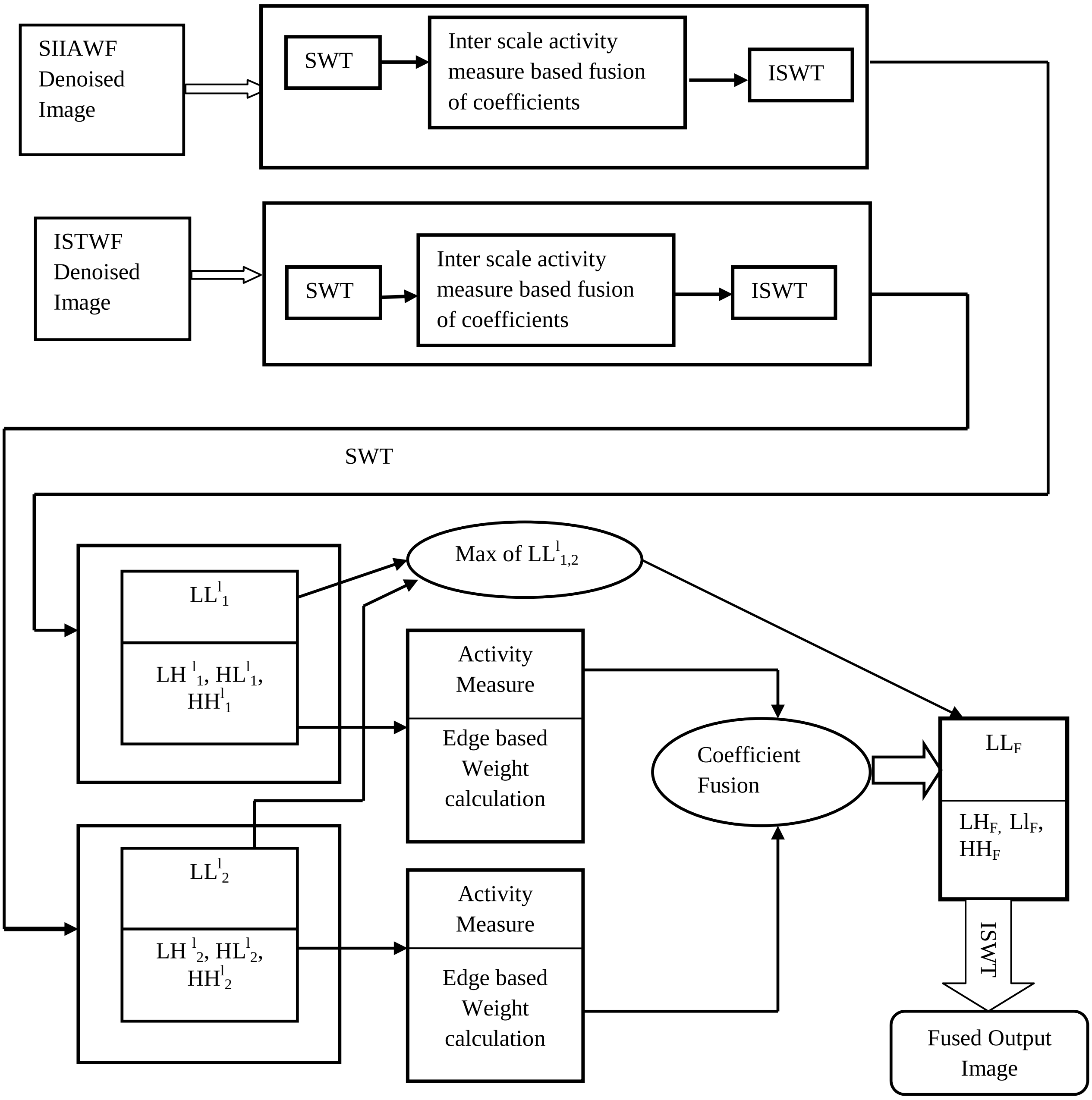

Figure 6.1 Block diagram of the proposed inter and intra-scale activity based fusion approach

Figure 6.1 shows the block diagram of the proposed fusion scheme. It performs a two level fusion process. The two denoised outputs from SIIAWF and ISTWF are taken as the source images. Let the source image $I_1(i,j)$ be the denoised image of SIIAWF and the source image $I_2(i,j)$ are the denoised image of ISTWF. The two images are decomposed using SWT to required number of levels $(l = 1.2...L)$. The approximation sub-bands of the source images are represented as LL_1 and LL_2. The detail subbands are $LH^l_{SI}, HL^l_{SI}, HH^l_{SI}$, where l represents the level of decomposition and SI represents the source images ($SI = 1,2$).

6.2.3 Inter-Scale Activity Based Fusion

Here, the fusion of the wavelet coefficients within each source image is carried out by applying an inter scale decision rule. The activity measure calculated is the entropy of detail subbands. The procedure is detailed below. Stationary Wavelet transform is applied to decompose the source images $I_1(i,j)$ and $I_2(i,j)$ into approximation and detail subbands. The detail subbands are then divided into 3x3 blocks and an activity measure of entropy is calculated for each block using Equation (6.1)

$$e^{lk}_{SI} = \frac{\ln \sqrt{\left(\dfrac{\mu^l_{SI} - \sum\limits_{i,j=1}^{3} I^{lk}_{SI}(i,j)}{\sigma^l_{SI}(i,j)} \right)^2}}{m} \tag{6.1}$$

where l represents the level of decomposition, SI represents the source images, k represents the block number, μ_{SI} and σ_{SI} are the mean and standard deviation of the decomposed source image coefficients respectively and m represents the block size equal to 3. For inter scale fusion of the coefficients, the following decision rule defined in Equation (6.2) is applied.

$$I_{SI}^{l,k}(i,j) = \begin{cases} I_{SI}^{l+1.k}(i,j) & \text{if} \quad (e_{SI}^{l+1,k}) > (e_{SI}^{l,k}) \\ I_{SI}^{l,k}(i,j) & \text{otherwise} \end{cases} \tag{6.2}$$

where l represents the level of decomposition and k represents the block number. The entropy of the coefficients in each 3x3 block, at level l, is compared with the corresponding block coefficients at level $l+1$ and the block with higher entropy is retained, for each of the source images. This process is repeated for three detail subbands, of the two source images. Then, inverse stationary wavelet transform is applied to reconstruct the inter-scale fused source images individually.

6.2.4 Intra-Scale Activity Based Fusion

At the second level, the interscale fused source images are subjected to SWT. The fusion process in this level is carried out by a new weighted entropy based activity measure of the two images. Weighted measure based activity has been studied by Yuan et al (2012) to fuse hyperspectral images and by several others. The weights are the edge measures determined based on the intra scale dependency of the wavelet coefficients within the subband.

Activity Measure calculation

The entropy is measured in blocks for all the detail subbands in the two source images using Equation (6.1). Then, for each of the detail subbands, an edge measure is determined within a neighbourhood (3x3) exploiting the intra scale dependency as in Equation (6.3),

$$v(i,j) = \frac{1}{NxN}\left|\left(W(i,j) - \mu(i,j)\right)\right| \tag{6.3}$$

where $v(i, j)$ is the weight measure, $W(i, j)$ is the wavelet coefficient and $\mu(i, j)$ is the mean calculated for each pixel around a local neighborhood. The calculated measure serves as a weight factor. The activity measure for fusing the two images is now the weighted entropy of the blocks in the detail subbands calculated as in Equation (6.4).

$$we_{SI}^{lk}(i, j) = v(i, j) * e_{SI}^{lk} \tag{6.4}$$

where $we_{SI}^{lk}(i, j)$ is the weighted entropy activity measure, $v(i, j)$ is the weight factor and e_{SI}^{lk} is the entropy calculated for each of the subband coefficients. The measure $v(i, j)$ utilize the edge clustering property to identify the edge pixels. Hence this measure combined with entropy keeps the edge pixels intact. Then, fusion of approximation and detail coefficients are carried out separately as detailed below.

Fusion of Detail subband coefficients

The detail subbands (horizontal, vertical and diagonal) of the two images $I_1(i, j)$ and $I_2(i, j)$ are fused using the weighted entropy activity measure. For getting fused image block, the coefficients from $I_1(i, j)$ is selected if its weighted entropy measure is greater than the weighted entropy of the corresponding block in $I_2(i, j)$ otherwise $I_2(i, j)$ is selected.

$$I_{FI}^{l,k}(i, j) = \begin{cases} I_1^{l,k}(i, j) * v(i, j) & \text{if} \quad (we_1^{l,k}) > (we_2^{l,k}) \\ I_2^{l,k}(i, j) * v(i, j) & \text{otherwise} \end{cases} \tag{6.5}$$

where $I_{FI}^{l,k}(i, j)$ is the fused subband coefficients, $we_1^{l,k}$ is the weighted entropy of the source image1 and $we_2^{l,k}$ is the weighted entropy of the source image2.

Fusion of LL subband coefficients

The LL subband coefficients are fused by retaining the maximum magnitude coefficient of the source images. The fusion rule for LL subband is given by,

$$I_{FI}^{A} = \max(I_1^A, I_2^A) \tag{6.6}$$

where I_{FI}^{A} is the approximation subband of the fused image , I_1^A is approximation subband of the IAWF image and I_2^A approximation subband of the ISTWF image.

Finally, inverse stationary wavelet transform is applied to the fused decompositions to reconstruct the fused image as given in Equation (6.7).

$$I_{FI} = \text{ISWT}\ (I_{FI}^{a}, I_{FI}^{h,}, I_{FI}^{v}, I_{FI}^{d}) \tag{6.7}$$

6.3 SUMMARY OF THE DENOISING ALGORITHM FOR FBWF

The steps involved in this fusion based denoising scheme are summarized as follows:

Step 1: Take the two denoised outputs from SIIAWF and ISTWF as source images

Step 2: The two source images are decomposed into approximation and detail subbands using SWT

- An entropy measure is determined for each of the detail subbands, Equation (6.1).

- Decision rule is applied from the coarser to finer scale coefficients and inter scale activity based fusion is achieved for each source image, Equation (6.2).
- The two source images are reconstructed separately

Step 3: Decompose the source images by applying SWT

- Fusion of detail coefficients

  For each of the details subbands in two source images,

  - An entropy measure is calculated as in Equation (6.1)
  - A weight measure is calculated using intra-scale dependency, Equation (6.3).
  - Weighted entropy measure is calculated using Equation (6.4).
  - Fusion of subband coefficients is carried out by a decision rule in Equation (6.5).

- Fusion of approximation coefficients

  - Fuse the approximation coefficients of the two images by finding the maximum at the corresponding locations.

Step 4: The fused subband coefficients are subjected to inverse stationary wavelet transform to reconstruct the fused output image.

6.4 RESULTS AND DISCUSSION

The performance evaluation of the FBWF is tested with synthetic phantom image with artificially simulated speckle and Figure 6.2 shows the comparison of output images with some of the existing filters.

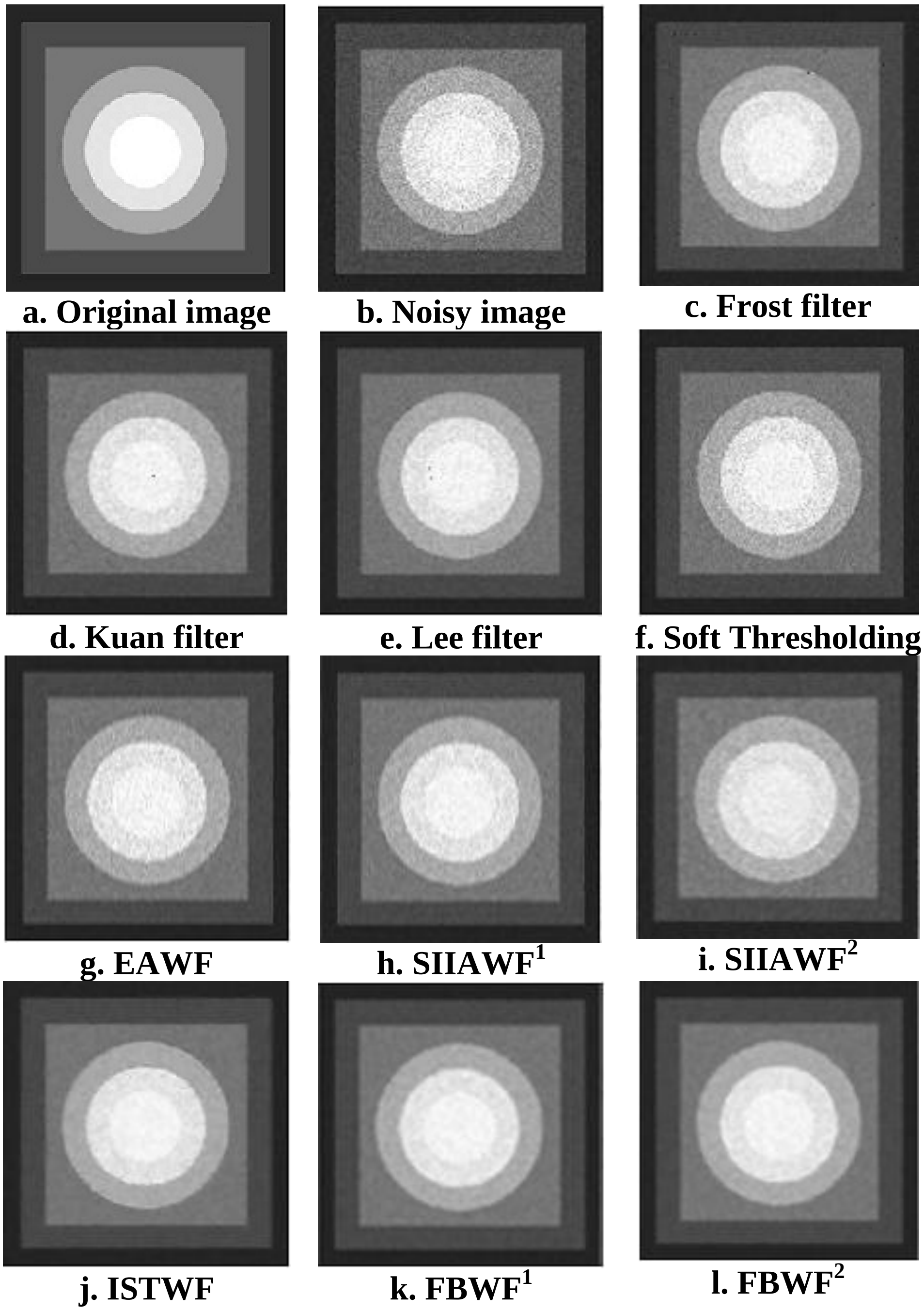

Figure 6.2 Comparison of visual quality of FBWF with existing filters for synthetic phantom image

The output images show that the performance of fusion based approach effectively increased the quality of the phantom image. The activity measure used in this FBWF is the entropy measure for inter-scale fusion at first level and weighted entropy for intra scale based fusion in the second level. Entropy is chosen as the activity measure based on the results of comparison between various activity measures like variance, kurtosis and entropy as shown in Table 6.1 for US image1. FBWF^1 represents the fusion of SIIAWF^1 and ISTWF and FBWF^2 represents the fusion of SIIAWF^2 and ISTWF.

Table 6.1 Performance comparison of FBWF for various activity measures

σ^2	Variance Fusion	Kurtosis Fusion	Entropy Fusion	FBWF^1	FBWF^2
				SIIAWF^1 +ISTWF	SIIAWF^2 + ISTWF
	Peak Signal to Noise Ratio				
0.01	36.1741	39.5513	41.9750	42.6639	43.6949
0.04	35.4600	37.9063	38.3291	40.1688	40.5067
0.08	34.7111	36.4754	36.8874	38.2874	39.3612
0.1	34.4914	35.9581	36.2356	37.8350	38.8116
	Mean Square Error				
0.01	15.6918	7.2102	4.1265	3.5212	2.7771
0.04	18.4961	10.5306	9.5536	6.2547	5.7864
0.08	21.9770	14.6399	13.3150	9.6459	7.5329
0.1	23.1171	16.4920	15.4712	10.7048	8.5490
	Structural Similarity Index Measure				
0.01	0.9446	0.9818	0.9825	0.9829	0.9837
0.04	0.9252	0.9558	0.9555	0.9559	0.9564
0.08	0.9042	0.9351	0.9390	0.9379	0.9443
0.1	0.8957	0.9305	0.9309	0.9313	0.9373
	Equivalent Number of Looks				
0.01	1.7249	1.7013	1.7193	1.7518	1.7706
0.04	1.7388	1.7225	1.7504	1.7795	1.7973
0.08	1.7435	1.7338	1.7505	1.7791	1.7987
0.1	1.7407	1.7405	1.7403	1.7773	1.8010
	Edge Preservation Index				
0.01	0.5542	0.5824	0.7120	0.7549	0.8085
0.04	0.4725	0.5343	0.5961	0.6736	0.7330
0.08	0.4551	0.5006	0.5578	0.6173	0.6965
0.1	0.4370	0.4967	0.5328	0.6015	0.6864

Table 6.2 Performance comparison of FBWF for various noise variances and filters

σ^2	Noisy	Frost	Kuan	Lee	Soft Thresholding	Qin	Andria	FBWF[1] SIIAWF[1] + ISTWF	FBWF[2] SIIAWF[2] + ISTWF
	Peak Signal to Noise ratio								
0.01	34.9435	38.6438	39.8387	39.7923	36.2507	40.4068	37.7669	42.6639	**43.6949**
0.04	31.4191	34.0636	35.5479	35.5193	33.1247	36.0805	36.4700	40.1688	**40.5067**
0.08	30.4078	31.8946	32.9930	32.8841	32.0909	34.4780	35.4882	38.2874	**39.3612**
0.1	30.1131	31.2677	32.0888	32.0758	31.7935	34.0053	35.1771	37.8350	**38.8116**
	Mean Square Error								
0.01	20.8321	8.8859	6.7485	6.8211	15.4175	5.9210	10.8379	3.5212	**2.7771**
0.04	46.8998	25.5104	18.1254	18.2455	31.6673	16.0335	14.6588	6.2547	**5.7864**
0.08	59.1965	42.0362	32.6425	33.4712	40.1782	23.1889	18.3705	9.6459	**7.5329**
0.1	63.3536	48.5639	40.1979	40.3180	43.0259	25.8553	19.7411	10.7048	**8.5490**
	Structural Similarity Index Measure								
0.01	0.9663	0.9804	0.9819	0.9820	0.9666	0.9822	0.9566	0.9829	**0.9837**
0.04	0.8882	0.9451	0.9512	0.9515	0.9135	0.9461	0.9148	0.9559	**0.9564**
0.08	0.8104	0.9023	0.9145	0.9124	0.8559	0.9068	0.8886	0.9379	**0.9443**
0.1	0.7815	0.8798	0.8944	0.8938	0.8311	0.8913	0.8692	0.9313	**0.9373**
	Equivalent Number of Looks								
0.01	1.6661	1.7021	1.6975	1.6994	1.6419	1.7094	1.6796	1.7518	**1.7706**
0.04	1.5483	1.6716	1.6844	1.6848	1.5643	1.6865	1.6761	1.7795	**1.7973**
0.08	1.4127	1.6304	1.6648	1.6636	1.4767	1.6631	1.6718	1.7791	**1.7987**
0.1	1.3606	1.6065	1.6564	1.6593	1.4347	1.6495	1.6699	1.7773	**1.8010**

Table 6.2 Continued

σ^2	Noisy	Frost	Kuan	Lee	Soft Thresholding	Qin	Andria	FBWF	
								SIIAWF[1] + ISTWF	SIIAWF[2] + ISTWF
	Edge Preservation Index								
0.01	0.3274	0.2622	0.2244	0.2213	0.3486	0.5470	0.5848	0.7549	**0.8085**
0.04	0.1722	0.1552	0.1646	0.1628	0.1759	0.2837	0.4527	0.6736	**0.7330**
0.08	0.1239	0.1085	0.1312	0.1262	0.1221	0.1966	0.4021	0.6173	**0.6965**
0.1	0.1114	0.0974	0.1100	0.1121	0.1072	0.1763	0.3892	0.6015	**0.6864**

From Table 6.1 it is seen that entropy based fusion gives a better output than variance and kurtosis based fusion approaches. Hence entropy measure is considered as an activity measure for the proposed FBWF. The results of the proposed FBWF are shown in last two columns of Table 6.1. The quantitative performance measures indicate that FBWF outperforms the variance and kurtosis based fusion approaches. The performance improvement is good for high noise variances (0.8 and 0.1).

The results of comparison of FBWF with the existing approaches for US image1 are furnished in Table 6.2. The FBWF is compared with standard spatial domain speckle filters, soft thresholding, Qin et al (2010) and Andria et al (2013) approaches. The FBWF is generated with two filters. The results in column 9 of Table 6.2 shows the output of $SIIAWF^1$ fused with ISTWF and Column 10 indicates the results of $SIIAWF^2$ fused with ISTWF. The quantitative performances are measured for simulation with US image1. For $SIIAWF^1$ and ISTWF based fusion (column 9), on an average, PSNR is increased by 1.23dB and 1.75dB; MSE is reduced by 24.15% and 32.78% and EPI is increased by 35.93% and 11.50% compared to $SIIAWF^1$ and ISTWF respectively. SSIM. ENL and EPI values show better improvement for high noise variances ($\sigma^2 = 0.08$ and 0.1).

For $SIIAWF^2$ and ISTWF based fusion (column 10) on an average, PSNR is increased by 0.44dB and 2.62dB; MSE is reduced by 20.06% and 45.02% and EPI is increased by 24.61% and 19.97% compared to $SIIAWF^2$ and ISTWF respectively. The SSIM values are much closer to unity for both low and high noise variances, indicating an improved preservation of structural similarity. The value of ENL is improved and better for high noise variance. The EPI measure shows more significant improvement than the other approaches considered. Therefore, the fusion of $SIIAWF^2$ with ISTWF offers an improved noise reduction with good edge preservation behaviour.

Table 6.3 presents the results of quantitative performance comparison of FBWF with the approaches described in this research work. The EAWF produced an improved performance for different noise variances. The SIIAWF[1] and SIIAWF[2] showed a better performance than EAWF in all respects. ISTWF showed a comparatively better performance in terms of PSNR and MSE, but yielded improved edge preservation. The fusion of SIIAWF and ISTWF combined these two performances and resulted in increased PSNR and EPI values. SSIM value of the fused output is increased for high noise variances than lower variances.

Table 6.3 Comparison of performance metrics for proposed filters

σ^2	Noisy	FILTER - I			FILTER-II	FBWF[1]	FBWF[2]
		EAWF	SIIAWF[1]	SIIAWF[2]	ISTWF	SIIAWF[1] + ISTWF	SIIAWF[2] + ISTWF
	Peak Signal to Noise Ratio						
0.01	34.9435	41.8515	42.2175	44.4192	41.8049	42.6639	43.6949
0.04	31.4191	38.4214	38.5345	40.0198	37.7036	40.1688	40.5067
0.08	30.4078	36.4853	36.8641	38.3227	36.4953	38.2874	39.3612
0.1	30.1131	35.7670	36.4357	37.8468	35.8921	37.8350	38.8116
	Mean Square Error						
0.01	20.8321	4.2455	3.9024	3.0004	4.2913	3.5212	2.7771
0.04	46.8998	9.3528	9.1124	7.5154	11.0336	6.2547	5.7864
0.08	59.1965	14.6068	13.3866	10.2651	14.5730	9.6459	7.5329
0.1	63.3536	17.2337	14.7745	11.1274	16.7443	10.7048	8.5490
	Structural Similarity Index Measure						
0.01	0.9663	0.9848	0.9854	0.9889	0.9840	0.9829	0.9837
0.04	0.8882	0.9608	0.9612	0.9655	0.9382	0.9559	0.9564
0.08	0.8104	0.9346	0.9377	0.9499	0.9149	0.9379	0.9443
0.1	0.7815	0.9210	0.9285	0.9419	0.9052	0.9313	0.9373
	Equivalent Number of Looks						
0.01	1.6661	1.7114	1.7131	1.7430	1.7281	1.7518	1.7706
0.04	1.5483	1.7125	1.7204	1.7565	1.7691	1.7795	1.7973
0.08	1.4127	1.7081	1.7286	1.7515	1.7660	1.7791	1.7987
0.1	1.3606	1.7013	1.7247	1.7466	1.7451	1.7773	1.8010
	Edge Preservation Index						
0.01	0.3274	0.5766	0.5979	0.6752	0.7048	0.7549	0.8085
0.04	0.1722	0.4285	0.4417	0.5410	0.5778	0.6736	0.7330
0.08	0.1239	0.3598	0.3407	0.5051	0.5379	0.6173	0.6965
0.1	0.1114	0.3308	0.3387	0.4922	0.5277	0.6015	0.6864

σ^2 **Noisy image** **FBWF Output image**

0.01

0.04

0.08

0.1

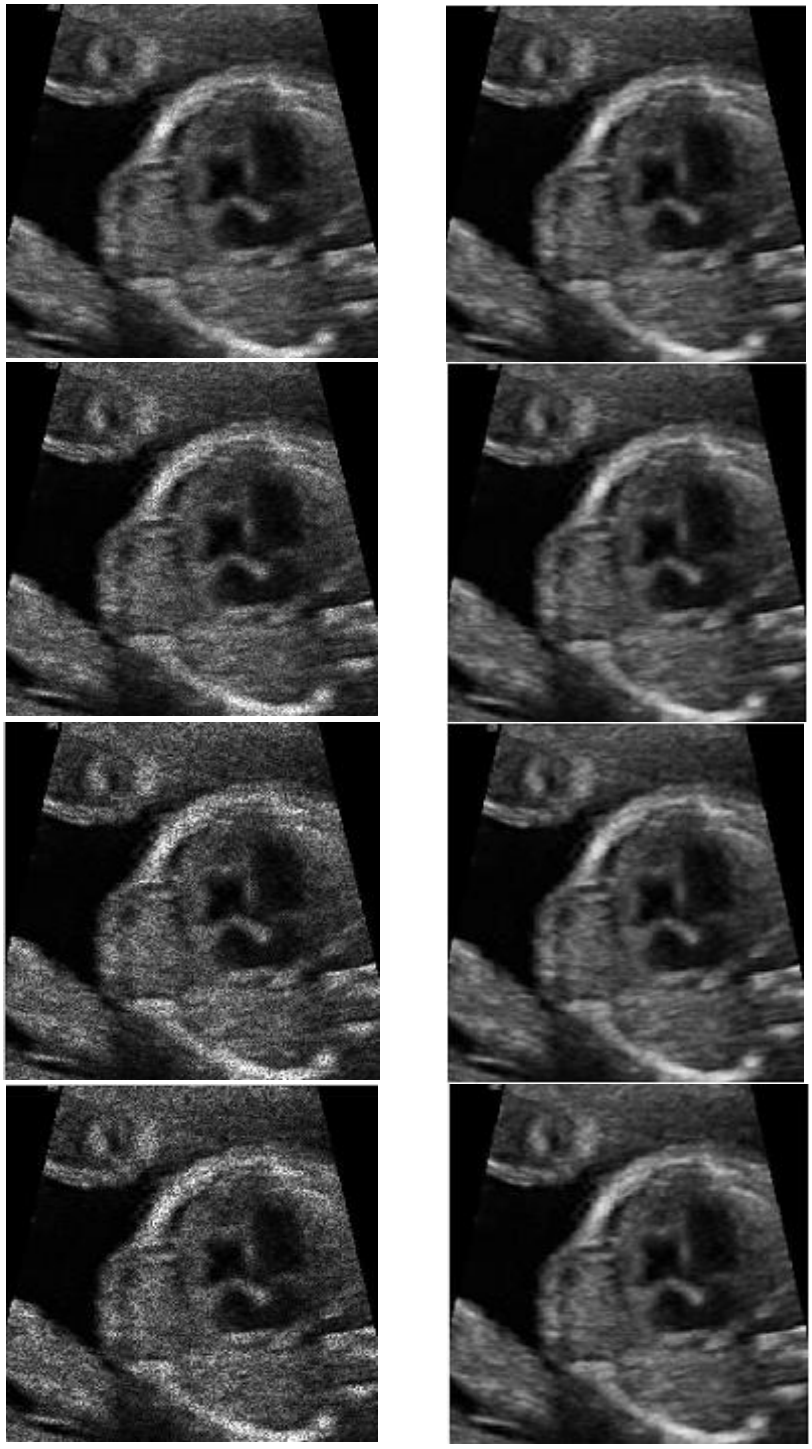

Figure 6.3 Comparison visual quality of FBWF for various noise variances for US image1

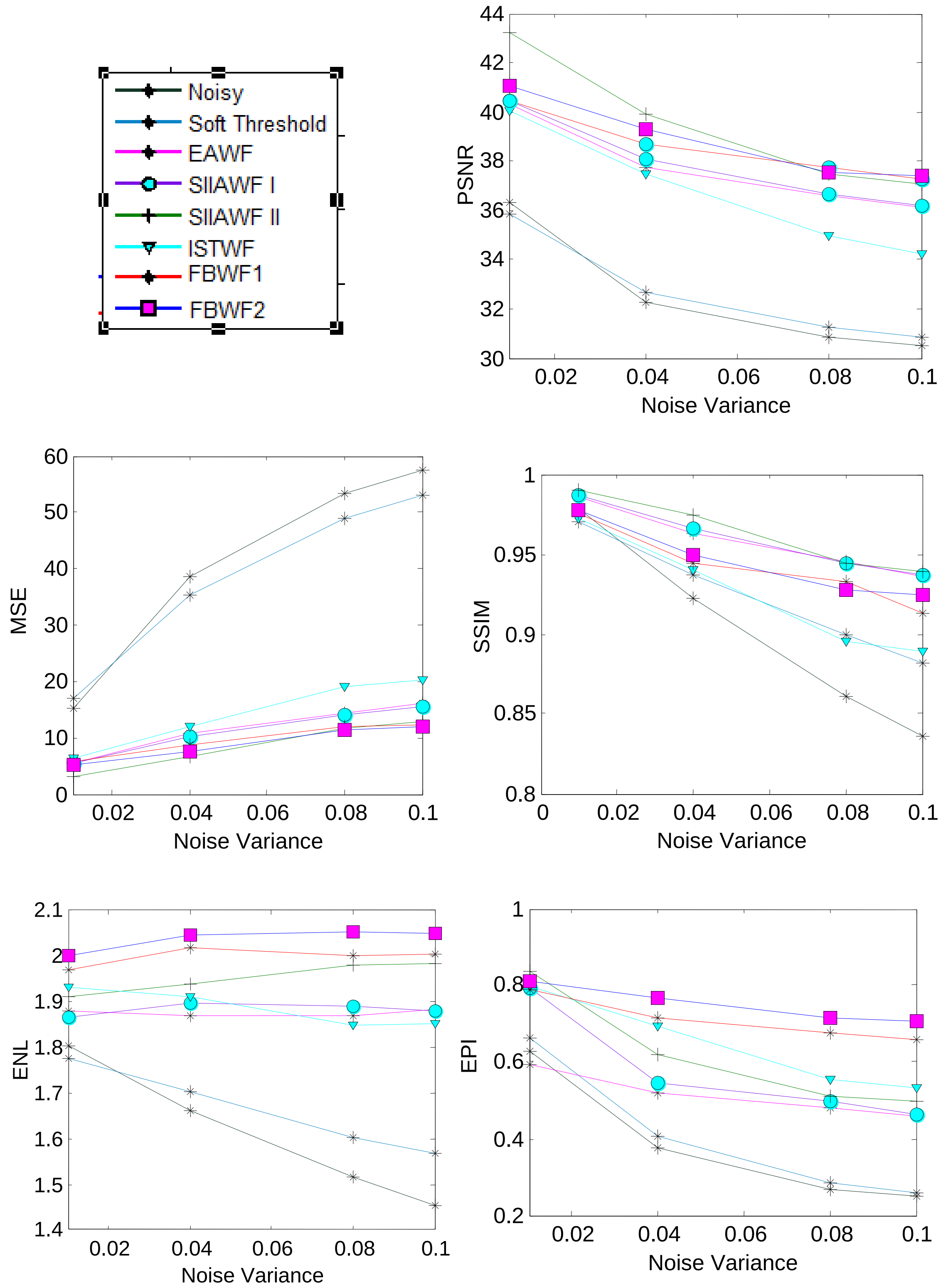

Figure 6.4 Graphical analysis of various performance measures of FBWF with proposed filters for US image2

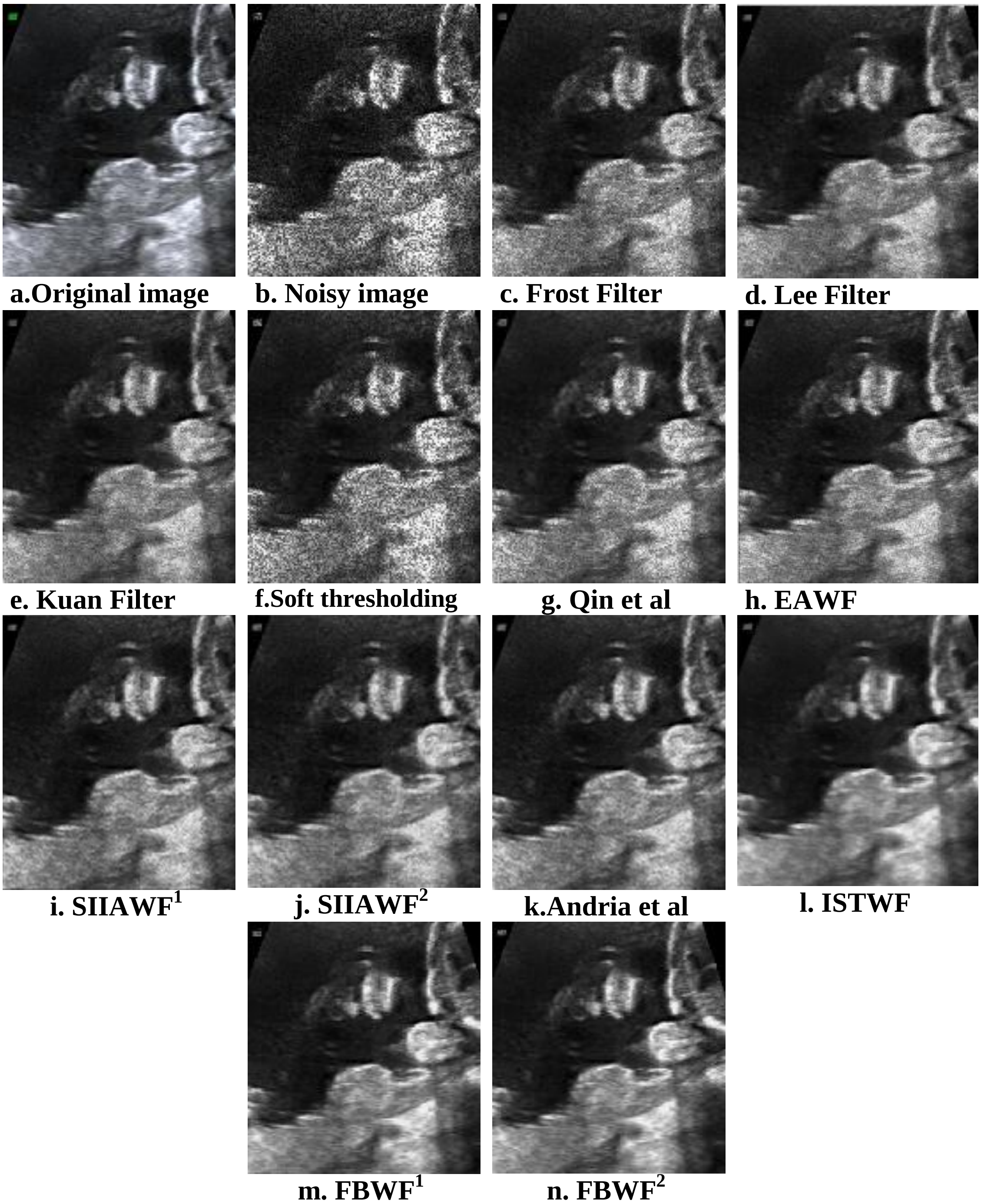

Figure 6.5 Visual quality comparison of FBWF with existing filters for US image3

Figure 6.3 shows the visual quality of FBWF simulated with US image1 for different noise variances. From the figures it is apparent that visual quality is better for all the noise variances.

The proposed fusion approach is tested with some more clinical US images. The qualitative performance analysis through graphical analysis is shown in Figure 6.4 for US image 2 for various filters. For this image, the fusion results for ENL and EPI measures are superior to the other filters, while PSNR and SSIM values are improved for high noise variances. Figure 6.5 shows a comparison of visual quality of US image3 with existing filters for US image 3. The images in 4^{th} row of Figure 6.5 show that the visual quality of FBWF is superior to the output images of various filters. The noise removal, feature preservation and contrast of the image are improved in the FBWF.

The visual quality of the images presented in Figures 6.3 and 6.5 clearly show the superior performance of the proposed scheme. Table 6.4 depicts the results of comparison of performance measures of FBWF for two types of fusion rules applied to the approximation coefficient fusion. Therefore, the proposed inter-scale and intra-scale activity based fusion resulted in better noise removal and increased edge preservation performance.

6.5 SUMMARY

A new fusion based wavelet filter is proposed in this chapter for enhancing the US images. A single stage fusion is followed in the existing approaches. The proposed FBWF performs a two level fusion, an inter-scale activity measure based fusion for the first level and intra-scale activity based fusion for the second level. The entropy measure is considered for fusing the details coefficients in the first level and weighted entropy is taken as the activity measure in the second level. The comparison of entropy measures in the adjacent scales aided in retaining the important image details at the first level. The factor used to weight the entropy utilizes the intra-scale correlation of the coefficients. As a result, the final fused image resulted in a good quality enhanced image with high PSNR, EPI and contrast enhancement.