A Comparative Analysis of Different Wavelets for Enhancing Medical Ultrasound Images

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ABSTRACT
Ultrasound imaging is one of the popular imaging modalities used frequently by medical practitioners for diagnosis of diseases. But the problem with this technique is its low-resolution and the presence of speckle noise. This makes it difficult for the medical practitioners in studying and properly diagnosing the disease. In the past, researchers have enhanced the medical ultrasound images using various techniques like spatial-domain filtering, frequency domain filtering, histogram processing, morphological filtering and wavelets. Among these, wavelet based techniques have proved to be superior as compared to the rest of the techniques for enhancing medical ultrasound images. In this paper, a comparative analysis of different wavelet families has been carried out for enhancing medical ultrasound images. We have investigated the performance of Haar, Daubechies, Coiflet and Symlet wavelets of various orders using different decomposition levels and threshold selection methods to determine which one yields better enhancement results. The performance is evaluated using objective image quality parameters like Mean Square Error (MSE) and Peak Signal to Noise Ratio (PSNR).

General Terms
Medical image processing, Image enhancement, Speckle.

Keywords
Wavelet, Discrete Wavelet transform, Wavelet thresholding, VisuShrink, SUREShrink.

1. INTRODUCTION
Among the various imaging modalities that are used in the medical field, ultrasound imaging is popular due to its non-invasive nature, low acquisition cost, and capability of forming real time imaging [1]. However, the quality of ultrasound images is degraded by the presence of signal dependent noise called as Speckle. Speckle noise is defined as the random mottling of the image with dark and bright spots which hides certain details [8]. This deteriorates the quality of such images thereby obscuring fine details and degrading the detection of low-contrast lesions. Thus it reduces the observer's ability to deduce actual information [10]. So in order to analyze medical ultrasound images properly, we have to enhance them. But this is quite difficult because removing speckle may remove some information which is of interest to an observer. So a trade-off has to be maintained while de-speckling ultrasound images [7].

For reducing speckle from ultrasound images, two techniques are commonly used - spatial filtering method and transform- domain based filtering method. Between these two methods, wavelet transform based method performs better due to its sparsity and multi-resolution properties [2]. Many attempts have been made in the past for enhancing ultrasound images. The use of wavelet transform is very popular in this area. In case of wavelet transform, we can analyze a given signal according to some scale.

In [8], Yong Sun Kim and Jong Beom Ra have proposed an algorithm based on multi-resolution approach where directional filtering was used for improving the continuity of ultrasound image edges and wavelet thresholding was used to reduce noise.

In [9], Peter C. Tay et al. have proposed a method for de-speckling ultrasound images which was based on removing outliers. By removing outliers, the method reduces the local variance of the image. Thus, the method produces a converging sequence of images by squeezing or compressing the stochastically distributed pixel values to some limiting value. As such, this method is called as squeeze box filter (SBF). This method is compared with the other well known despeckling filters and results show superior contrast enhancement.

In [10], Banazier A. Abrahim and Yasser Kadah have proposed a new speckle reduction technique for the enhancement of ultrasound images. This method was based on combining total variation (TV) method and wavelet shrinkage. In this method, a noisy image is decomposed into sub-bands of LL, LH, HL, and HH in wavelet domain. LL sub-band contains the low frequency coefficients along with less noise, which can be easily eliminated using TV based method. More edges and other detailed information like textures are contained in the other three sub-bands, and for that a shrinkage method based on the local variance to extract them from high frequency noise is used.

In [12], P.S. Hiremath et al. have compared the performances of the multi-scale methods - wavelet transform, Laplacian pyramid transform and contourlet transform for de-speckling medical ultrasound images. In [13], Olawuyi et al. have examined the performance of four wavelets – Haar, db4, Dmey, coif3 and sym4 for de-noising a cardiac Magnetic Resonance Image (MRI) using the Mean Square Error (MSE) and Peak Signal to Noise Ration (PSNR) as the evaluation factors.

The organization of the paper is as follows. In the section II, discrete wavelet transform and wavelet based thresholding techniques are presented. In section III, the methodology used to enhance ultrasound images using different wavelet families is discussed. Section IV presents the experimental results.

2. TECHNIQUES USED IN THE PROPOSED WORK

In the section, we discuss the techniques used in the proposed work for the enhancement of medical ultrasound images, namely - discrete wavelet transform and wavelet thresholding. Recently, discrete wavelet transform has gained much interest in image de-noising area. The DWT can be interpreted as decomposing a signal into a set of independent, spatially oriented frequency channels [5]. The discrete wavelet transform maps an image into a set of coefficients that constitute a multi-scale representation of the image. Some of these coefficients represent noise and other represent the actual signal. By suitably modifying these coefficients using different threshold methods, the noise can be reduced. The image is then reconstructed using these modified wavelet coefficients. This process is called as inverse wavelet transform. This results in an enhanced ultrasound image whose quality is better than the speckled image. This whole process is summarized below.

1. To compute the wavelet transform of the speckled image to get the wavelet coefficients using the Discrete Wavelet Transform (DWT).
2. To Threshold the wavelet coefficients obtained in the step 1 using different threshold methods in order to remove the coefficients that correspond to noise.
3. To computation the inverse Discrete Wavelet Transform (IDWT) to reconstruct the de-speckled image.

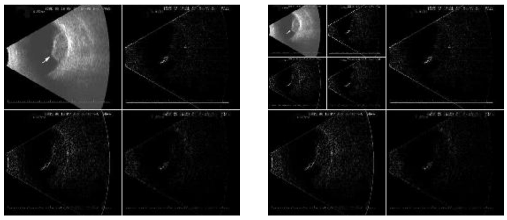
These techniques are discussed below.

2.1 Discrete Wavelet Transform

A wavelet is a waveform of limited duration that has an average value of zero. Unlike sinusoids that extend from minus to plus infinity, wavelets have a beginning and an end [11]. Wavelets come in various shapes and sizes. By stretching and shifting the wavelet, we can match it to the hidden event and thus discover its frequency and location in time. When shifted and stretched appropriately, a wavelet can match the given event very well.

The basic idea of the wavelet transform is to represent any arbitrary function (t) as a superposition of a set of such wavelets or basis functions [11]. These wavelets are obtained from a single prototype wavelet called the mother wavelet, by dilations or contractions (scaling) and translations (shifts).

From the view of point of images, discrete wavelet transform is a procedure that decomposes a given image into several frequency bands by using wavelet and scaling functions. Its digital implementation can be easily done by low-pass filtering and high-pass filtering and decimation. In the first stage of the decomposition, the image is split into 4 sub-bands, namely the HH, HL, LH and LL sub-bands **[**3**]**. The HH sub-band gives the diagonal information of the US image; the HL sub-band gives the horizontal features while the LH sub-band represents the vertical structures of the US image. The LL sub-band is the low-resolution residual consisting of low frequency components. In the next step, the LL sub-band is further divided at the higher levels of decomposition [6]. Fig 1 below shows 1-level and 2-level wavelet transforms of an image.



(a) (b)
Fig 1: Examples of wavelet transform
(a) One-level (b) Two-level

The given image is decomposed by low and high-pass filtering along the rows and the results of each filter are down-sampled by a factor of 2. For an image of image N by N, we get two sub-images that correspond to the low and high frequency components along the rows and each has the size N by N/2. Then each of these sub-signals is again low and high pass filtered along the columns. The results are again down-sampled by a factor of 2. Fig 2 shows level-1 decomposition of a two-dimensional image.

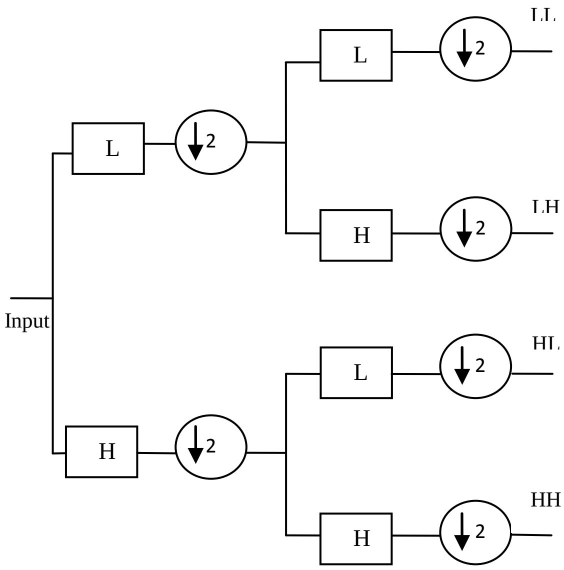


Fig 2: Level-1 decomposition of a two-dimensional image

2.2 Wavelet Based Thresholding

The work on filtering noise using wavelet thresholding was pioneered by Donoho and Johnstone. The wavelet transform is combination with the thresholding concept becomes a powerful de-noising tool for speckle reduction in medical images. The wavelet transform of an image typically consists of a large number of small coefficients (contain little information) and a small number of large coefficients (contains significant information). The large coefficients mainly represent signal whereas the smaller ones represent the noise [7]. By suitably modifying the coefficients, the noise can be reduced. The term wavelet thresholding can be defined as the decomposition of an image into its wavelet coefficients, comparing the detail coefficients with a given threshold value and then shrinking these coefficients close to zero to minimize the effect of noise in the data. The image is then reconstructed using these modified wavelet coefficients. The different methods of wavelet de-noising investigated so far differ only in the selection of the threshold. The basic assumption in wavelet de-noising technique is to remove small coefficients, which occurs most likely from noise signals [13].

There are two types of thresholding - hard thresholding and soft thresholding. The hard thresholding sets any coefficient less than or equal to the threshold *t* to zero. The coefficients greater than the threshold value *t* are not modified.

$$T_H = \begin{cases} x, for\ |x| \geq t \\ 0, otherwise \end{cases} \quad (1)$$

On the other hand, the soft thresholding sets any coefficient less than or equal to the threshold *t* to zero. The threshold *t* is subtracted from any coefficient that is greater than the threshold. Thus, the soft thresholding shrunks toward zero all those coefficients which are greater than the threshold value t.

$$T_s = \begin{cases} sign(x)(|x| - t), for\ |x| \geq t \\ 0, otherwise \end{cases} \quad (2)$$

Further, the threshold can be classified as either global or sub-band dependant. In case of global thresholding, a single threshold value is used whereas in case of sub-band dependant thresholding, separate threshold values are selected for each level namely LH, HL and HH sub-bands. Examples of each of these thresholding types include VisuShrink and SUREShrink methods.

The VisuShrink method was introduced by Donoho [6]. This method uses a threshold value t which is proportional to the standard deviation of the noise. It is based on the hard thresholding rule. It is also referred to as universal threshold and is defined as

$$T_U = \sigma\sqrt{2logn} \quad (3)$$

where σ represents the noise variance of the signal and n represents the signal size or the number of pixels in the image. The noise level is estimated on the basis of the median absolute deviation and is given by

$$\sigma = \frac{median(\{|g_{j-1,k}|:k=0,1,2.....,2^{j-1}-1\})}{0.6475} \quad (4)$$

where $g_{j-1,k}$ represents the detail coefficients in the wavelet transform. VisuShrink is a global thresholding scheme that uses a single value of threshold which is applied globally to all the wavelet coefficients.

On the other hand, SUREShrink method uses a threshold value that is based on Stein's Unbiased Risk Estimator (SURE). It is a combination of Universal threshold and the SURE threshold. This is a level-dependant thresolding method that specifies a threshold value t_j for each resolution level j in the wavelet transform. The SUREShrink threshold T_{SURE} is given by

$$T_{SURE} = min(t, \sigma\sqrt{2logn}) \quad (5)$$

where t denotes the value that minimizes the Stein's Unbiased Risk Estimator, σ is the noise variance calculated using (4) and n is the size of the image. SUREShrink follows soft thresholding and is smoothness adaptive.

3. PROPOSED WORK

Although a number of wavelets are available and have been used in the past for enhancement purpose, we have evaluated the performance of various wavelets using different levels of decomposition and threshold selection methods for different values of speckle noise v.

The process of image enhancement using wavelet-based technique is carried out using the following steps:

I. Preprocess the input ultrasound image (resize and conversion to grayscale).
II. Add speckle noise to the preprocessed image using different values of variance viz. v=0.03, 0.04 and 0.05.
III. Compute the discrete wavelet transform of the speckled image using different wavelet families - Haar, Coif3, Coif5, Sym5, Sym7, Db4 and Db6.
IV. Threshold the wavelet coefficients obtained in the previous step using the two threshold methods - VisuShrink and SUREShrink.
V. Compute the inverse wavelet transform to get back the modified image.
VI. Compute the performance parameters of the output image to perform comparisons.

The wavelet-based algorithm for enhancing medical ultrasound images is shown below in fig 3.

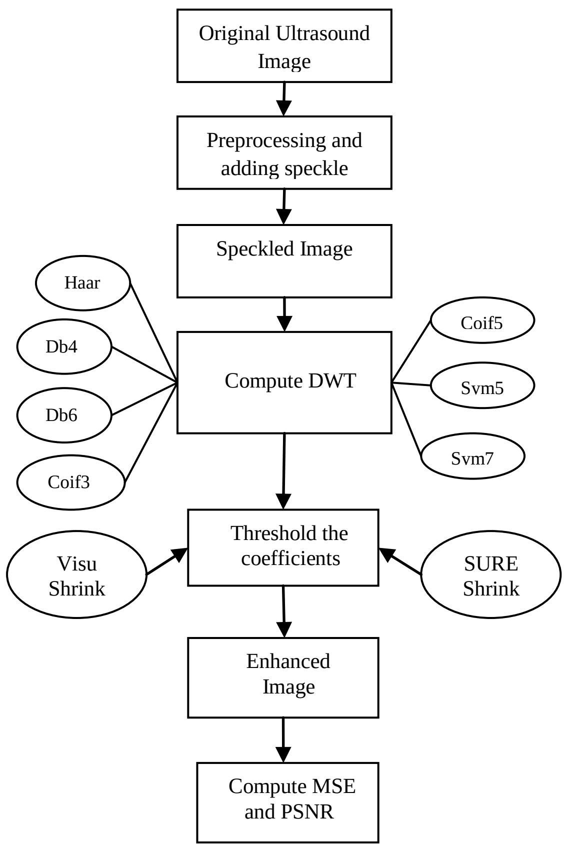


Fig 3: Methodology used for wavelet based enhancement

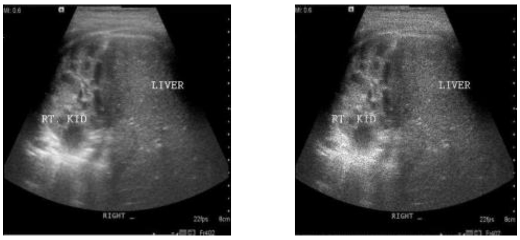
The algorithm accepts as input an ultrasound images to which different levels of speckle noise is added to further degrade it quality. The DWT is applied on this noisy ultrasound image. This process is carried out using four wavelet families namely, Haar, Daubechies, Coiflet and

Symlet using different levels of decomposition. The output of DWT produces wavelet coefficients representing noise/signal details. The next step is to perform thresholding. This is carried out using two different methods - VisuShrink and SUREShrink. To generate the enhanced image, the corresponding inverse DWT is applied on the modified wavelet coefficients. Finally, the output image is evaluated using objective quality parameters like MSE and PSNR. The wavelet functions used are- Haar, Coif-3, Coif-5, Sym-5, Sym-7, Db4 and Db6. Each of these wavelets is tested in combination with different levels of decomposition and threshold methods for enhancing ultrasound images corrupted with different levels of speckle noise.

4. EXPERIMENTAL RESULTS

The ultrasound images used in the experiments are mostly related to different abdominal parts like kidney and gall-bladder. These images have been converted to gray scale and resized to 512 × 512 before the actual experiments are performed. Further, to check the effectiveness of the different wavelet families, different levels of speckle noise have been added to these ultrasound images. The experiments for image enhancement were carried out using MATLAB software, version 7.8.0.347 (R2009a).

The performance of different wavelets was evaluated in terms of MSE and PSNR for the test image shown in fig 4.



(a) **(b)**

Fig 4: Test Image (a) Original Image (b) Speckled Image (v=0.03)

The image quality metrics are calculated as

$$MSE = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(x(m,n) - x'(m,n))^2 \qquad (6)$$

$$PSNR = 10log_{10}\frac{255^2}{MSE} \qquad (7)$$

The table 1 shows the results after applying different wavelets on the test image having speckle noise with variance v=0.03 at level 1 using two different threshold methods.

At level 1, it was observed that the Coiflet wavelet (Coif-5) outperformed the rest of the wavelets families in both the threshold methods in terms of PSNR. As far as the threshold method is concerned, it is observed that the various wavelets produce better results for the SUREShrink method. Similar results were obtained for v=0.04 and 0.05.

After enhancing images at decomposition level 1, we increased the decomposition level to 2 and investigated the results obtained after performing the same experiments on the test image with v=0.03. The results obtained are shown in table 2.

Table 1: Results at level 1 with v=0.03

Type of Wavelet	Level of Decomposition = 1, Variance = 0.03			
	VisuShrink		SUREShrink	
	MSE	PSNR (db)	MSE	PSNR (db)
Haar	72.3302	29.5376	71.3577	29.5964
Coif3	65.0223	30.0002	62.2967	30.1862
Coif5	64.2340	**30.0532**	61.7213	**30.2265**
Sym5	65.8643	29.9443	63.0889	30.1313
Sym7	64.2974	30.0489	61.7493	30.2245
Db4	65.3084	29.9811	62.1332	30.1976
Db6	65.4742	29.9701	62.6207	30.1636

Table 2: Results at level 2 with v=0.03

Type of Wavelet	Level of Decomposition = 2, Variance = 0.03			
	VisuShrink		SUREShrink	
	MSE	PSNR (db)	MSE	PSNR (db)
Haar	64.1037	30.0620	85.7657	28.7977
Coif3	57.2418	30.5537	66.7963	29.8833
Coif5	56.5241	30.6085	66.2425	29.9194
Sym5	57.0241	30.5702	67.4686	29.8398
Sym7	54.8487	**30.7391**	63.1171	**30.1293**
Db4	56.7438	30.5916	64.7221	30.0203
Db6	57.2895	30.5501	67.2736	29.8524

The results are different at level 2. It was observed that the Symlet wavelet (Sym-7) outperformed the rest of the wavelets families in both the threshold methods in terms of PSNR. As far as the threshold method is concerned, it is observed that at level 2 the various wavelets produce better results for the VisuShrink method. Moreover, similar results were obtained when the test image is corrupted with speckle with v=0.04 and 0.05.

Next we compared the results of 1st and 2nd levels of decomposition to find out which one gives better enhancement results. From the results obtained at two levels with variance v=0.03, we get the graph as shown in fig 5.

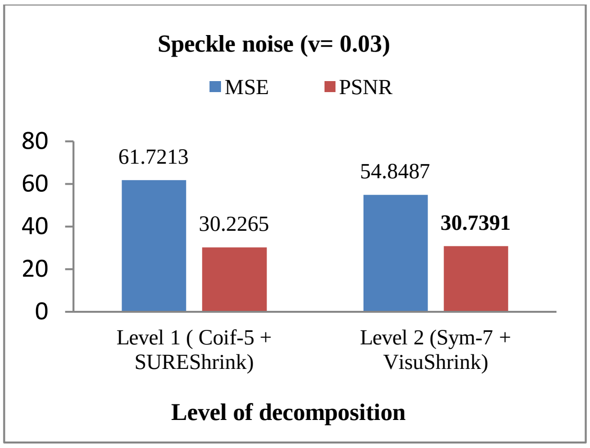


Fig 5: Comparison of MSE and PSNR for Level 1 and Level 2 using v=0.03

After comparing results at level 1 and 2, it was found that the 2nd level of decomposition produces better enhancement results as compared to the 1st level of decomposition for v = 0.03, 0.04 and 0.05. So, the better enhancement of ultrasound images is achieved if we use Symlet wavelet (Sym-7) in combination with the VisuShrink method.

5. CONCLUSION

Medical ultrasound images have the problem of speckle noise which degrades its visual appearance thereby making it difficult to properly diagnose the problem. A number of different techniques have been used in the past to address this problem. In this work, we have focused on the wavelet based enhancement and carried out a performance comparison of different wavelet families for enhancing medical ultrasound images. The experimentation was done using different decomposition levels and different threshold selection methods for various noise levels. It was observed that the Coiflet wavelet with order 5 i.e. Coif-5 outperformed the rest of the wavelet families at level 1 while the Symlet wavelet (Sym-7) is better than the rest of wavelet families at level 2 of decomposition. The 3rd level of decomposition resulted in over smoothening of ultrasound images. The 2nd level of decomposition produces better results as compared to the 1st level. Symlet wavelet (Sym-7) and VisuShrink method together at second level of decomposition produce the best enhancement results. Moreover, the PSNR value is highest when the speckle noise is least (v=0.03) and is lowest when the speckle noise is high (v=0.05).

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