Denoising Algorithms for Speckle Noise Reduction in Ultrasound Images

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Introduction

Ultrasound imaging is a common medical imaging technique practiced, especially for fetal imaging. It relies on transmitting ultrasound waves, or sound waves at higher frequencies than humans are capable of hearing, and receiving the waves that reflect back at interfaces with differences in impedance. These signals can be represented through A-mode, in which echos are plotted as a function of depth, or B-mode, where a slice of the body can be viewed as a two-dimensional image [1]. B-mode images are widely used in ultrasound imaging, and due to their relevance to the medical field, this report will focus on processing B-mode type images. While ultrasound imaging is popularly used due to its low cost, convenience, and non-ionizing properties, it lacks in its image quality resulting from the presence of noise. From the inherent properties of ultrasound waves, backscattering of the tissue undergoes random constructive and destructive interference that create an unwanted textured or grainy visual effect [2]. This noise pattern consists of bright and dark dots and is referred to as speckle noise. It can impede clinical diagnoses by reducing resolution and contrast in the image [3].

Speckle noise is multiplicative and non-Gaussian in nature [4], unlike other noise models we have explored throughout the course. Through experimental testing outlined in this report, we will explore novel algorithms that are commonly applied to reduce speckle noise and improve image quality of ultrasound images, such as the median filter and discrete wavelet transform denoising. New methods of denoising will also be introduced and compared to existing algorithms. The ultrasound images that are used for testing are drawn from online data sets of the carotid artery [5] and fetal head imaging [6].

Methods

In order to compare the performance of various de-speckling methods, speckle noise must be simulated on the ultrasound images gathered from the data sets. Two ultrasound images were obtained from the data set - one from the carotid artery collection and one from fetal head imaging collection. The speckle noise is multiplicative and modeled by a Rayleigh distribution [7]. The resulting image is characterized by the following equation:

$$I(x,y) = S(x,y) * N(x,y) \quad \text{(Eq. 1)}$$

where $I(x,y)$ is the resulting image containing speckle noise, $S(x,y)$ is the original noise-free image, and $N(x,y)$ is the speckle noise following a Rayleigh distribution. In this experiment, five variations of denoising algorithms are implemented and tested from two common de-speckling algorithms: the median filter and DWT denoising.

Median Filter

The median filter is a non-adaptive speckle filtering method, in which the value of each pixel of the image is transformed to be the median of pixel values in a specified area. This is similar to the averaging, or "box," filter. While it requires more processing power than the traditional averaging filter due to its non-linear representation, the median filter is less susceptible to skewing in the presence of outliers. A 3x3 window was used in applying the filter in order to allow for denoising capabilities while preserving some of the inherent textural properties of the tissues scanned by the ultrasound system.

Discrete Wavelet Transform Denoising

The discrete wavelet transform (DWT) denoising algorithm has also been used for speckle denoising due to recent advances with its applications in ultrasound imaging. Transforming an image into the wavelet domain compresses the intensities of pixel values into a more compact range. From there, noise can be better removed by zeroing the wavelet coefficients that are less than a specified threshold level. Rather than thresholding the wavelet coefficients based on a percentile, as was done in class, different thresholding methods [2] will be implemented and explored for de-speckling purposes.

Hard Thresholding

Hard thresholding is represented by the following expression:

$$\eta(w) = \begin{cases} w & |w| \geq T \\ 0 & |w| < T \end{cases} \quad \text{(Eq. 2)}$$

where η(w) is the filtered wavelet transform of the image, w is the wavelet coefficient, and T is the threshold value. We will refer to DWT denoising with hard thresholding as hard DWT denoising. The performance of various T values ranging from 0 to 1 was compared in order to find an optimized threshold that reduced the speckle noise level while preserving the integrity of the original image.

Soft Thresholding

Soft thresholding is represented as:

$$\eta(w) = \begin{cases} w - \mathrm{sgn}(w)T & |w| \geq T \\ 0 & |w| < T \end{cases} \quad \text{(Eq. 3)}$$

where sgn(w) is the sign function:

$$\mathrm{sgn}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ -1 & x < 0 \end{cases} \quad \text{(Eq. 4)}$$

We will refer to DWT denoising with soft thresholding as soft DWT denoising.

Soft thresholding is more commonly used in practice [2], as it is not as harsh and abrupt as the hard thresholding. Because it avoids the discontinuities produced by the hard thresholding function, soft thresholding may produce images that are more visually pleasing to the eye [4].

Due to the multiplicative nature of speckle noise, a logarithmic transformation is performed as a preprocessing step [2] to separate the image into additive components before the wavelet denoising algorithm is applied.

$$\log(I) = \log(S*N) = \log(S) + \log(N) \quad \text{(Eq. 5)}$$

This transformation is done because wavelet denoising performs best on additive noise. The steps implemented for the wavelet transform denoising process is summarized:

1. Take the logarithmic transform of (I(x,y)+1)
2. Perform the DWT of I(x,y)
3. Threshold using the hard or soft thresholding method
4. Perform the inverse DWT
5. Take the exponent to reverse the logarithmic preprocessing step and subtract offset

To avoid the issue of attempting to compute the logarithm of a zero-value pixel, the logarithm of the image plus one was taken. This was accounted for after the inverse DWT.

New Methods for De-Speckling

We propose to implement a sequential combination of the two non-linear methods above: median filtering and DWT denoising. Specifically, the sequence of performing the median filtering followed by soft DWT denoising, as well as the reverse of performing soft DWT denoising followed by median filtering, were tested. Both filtering methods are nonlinear methods, so the order of filtering is nontrivial. While both median filtering and soft DWT denoising could stand alone as functioning de-speckling algorithms, the combination of the two has the potential to make up for the individual drawbacks of each method. The median filter does a good job removing noise, but tends to remove too much texture, while the soft DWT denoising removes some noise, but leaves the image with a lot of residual speckles. We propose that the combination of both filters may do a better job than doing each filter individually.

Quantifying Performance

After artificially stimulating speckle noise, five methods of de-speckling were tested and compared. The root mean squared error (RMSE) is used to quantify the effectiveness of the denoising algorithm. The RMSE between the output of each de-speckling method and original image without added noise was compared to the RMSE between the noisy, unfiltered image and the original image. A reduction in RMSE after filtering is how we will quantitatively show success in reducing the speckle noise.

In addition to a quantitative report, a qualitative approach was also taken to describe the results. While one denoising method may significantly reduce RMSE, it may cause artifacts or too much blurring, resulting in greater distortion of the image and unsatisfactory results.

Results and Discussion

DWT Threshold Optimization

Utilizing various threshold functions (hard and soft) with different threshold values T produced different levels of denoising. Table 1 and Figure 1 display the calculated RMSE under these variable threshold conditions for the carotid artery image and the fetal head image. From a quantitative perspective, the RMSE for both hard thresholding and soft thresholding decreases as T increases, signaling that more noise is reduced. This trend is predicted, as larger T values remove more wavelet coefficients afflicted with speckling. The results also show that the soft thresholding method denoises speckled images better than hard thresholding. This is consistent with the different thresholding functions implemented, as hard thresholding is more harsh and produces more unnatural results. However, there is a limit to the effectiveness of increasing the value of T used for soft thresholding. As Figure 1 demonstrates, the RMSE does not decrease indefinitely and tends to plateau at around T = 1.0. Increasing T past this point will eventually lead to an increase in RMSE, as the thresholding in DWT denoising would remove significant wavelet coefficients and detract important features of the image.

Table 1. Comparison of RMSE for various threshold levels for hard and soft DWT thresholding. T=0 is analogous to the absence of a denoising algorithm.

	RMSE			
	Carotid Artery		*Fetal Head*	
T	**Hard Thresholding**	**Soft Thresholding**	**Hard Thresholding**	**Soft Thresholding**
0	54.92	54.92	49.94	49.94
0.1	54.91	46.08	49.92	41.91
0.2	54.71	39.01	49.70	35.50
0.3	54.20	33.38	49.17	30.37
0.4	53.45	28.93	48.39	26.22
0.5	51.91	25.47	47.15	22.91
0.6	50.20	22.84	45.63	20.30
0.7	47.92	20.92	43.63	18.29
0.8	45.72	19.57	41.62	16.80
0.9	43.91	18.70	39.53	15.77
1.0	41.91	18.20	37.25	15.12

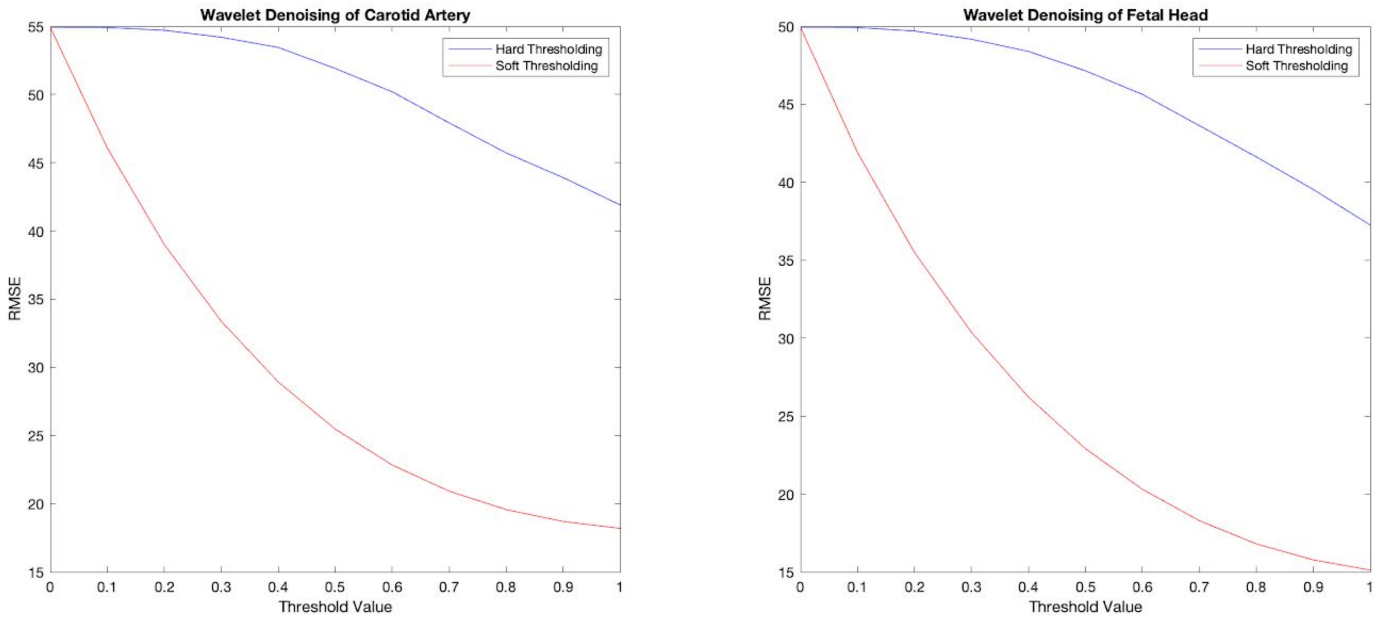


Figure 1. RMSE comparison at various threshold values for denoising carotid artery and fetal head ultrasound images.

In addition, when the visual output of the denoising algorithms is examined further in Figure 2, it is observed that artifacts begin to form as T increases for the soft thresholding method. The soft thresholding function (Eq. 3) produces larger offsets within the wavelet coefficients with a larger T, and as a result, it appears that blurred blocks are introduced to portions of the image. In considering these distortions and the reduction of RMSE with increased values of T, a compromise must be made in selecting the optimal threshold level to implement the DWT denoising algorithm with. A T value of 0.4 minimizes the block-like artifacts that appear while significantly reducing the RMSE levels. Thus, we use the soft thresholding procedure with a threshold of T = 0.4 to optimally de-speckle with the DWT denoising method.

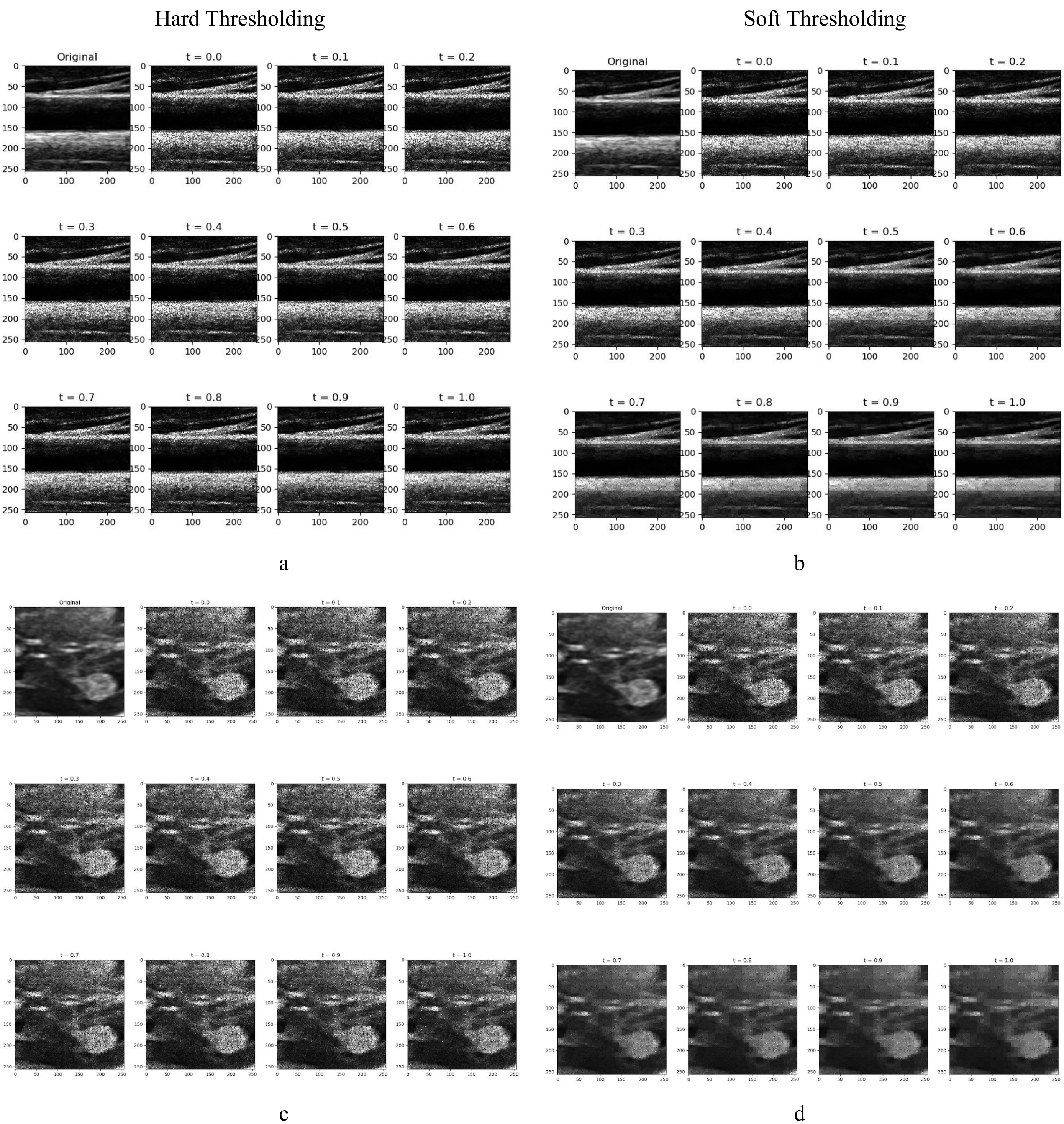
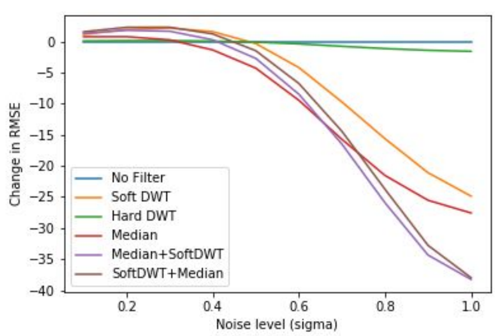


Figure 2. Ultrasound images of the carotid artery (a, b) and fetal head (c, d) processed using various DWT threshold functions.

Noise Level Results

The amount of success by the filters varies with the scale (also referred to as sigma) of the speckle noise. At particularly low variances (sigma < 0.4), none of the filtering methods succeeded at reducing the RMSE between the original ultrasound image and the filtered image with speckle noise. This may be due to the fact that at low scales, the Rayleigh distributed random multiplicative noise has a low mean, causing many of the pixels to become much dimmer than before. This effect was unable to be fixed by the filtering methods. As the scale of the speckle noise increased above, the five different filtering methods tended to get significantly better at removing the speckle noise, using RMSE as a metric.

Fetal



Carotid

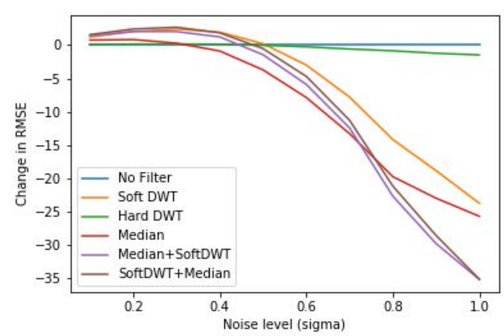


Figure 3. Change in RMSE between filtered and unfiltered image with respect to the original image as a function of noise level

The filtering methods performed very similarly between both images (fetal and carotid). The combination of median filtering and soft DWT filtering proved to be most successful at reducing the RMSE between the original ultrasound image and the filtered ultrasound image with speckle noise. For the DWT methods, the chosen threshold was 0.4, and was chosen to be a balance between reducing the RMSE and limiting the amount of blocking artifacts as seen in wavelet denoised images with high thresholds.

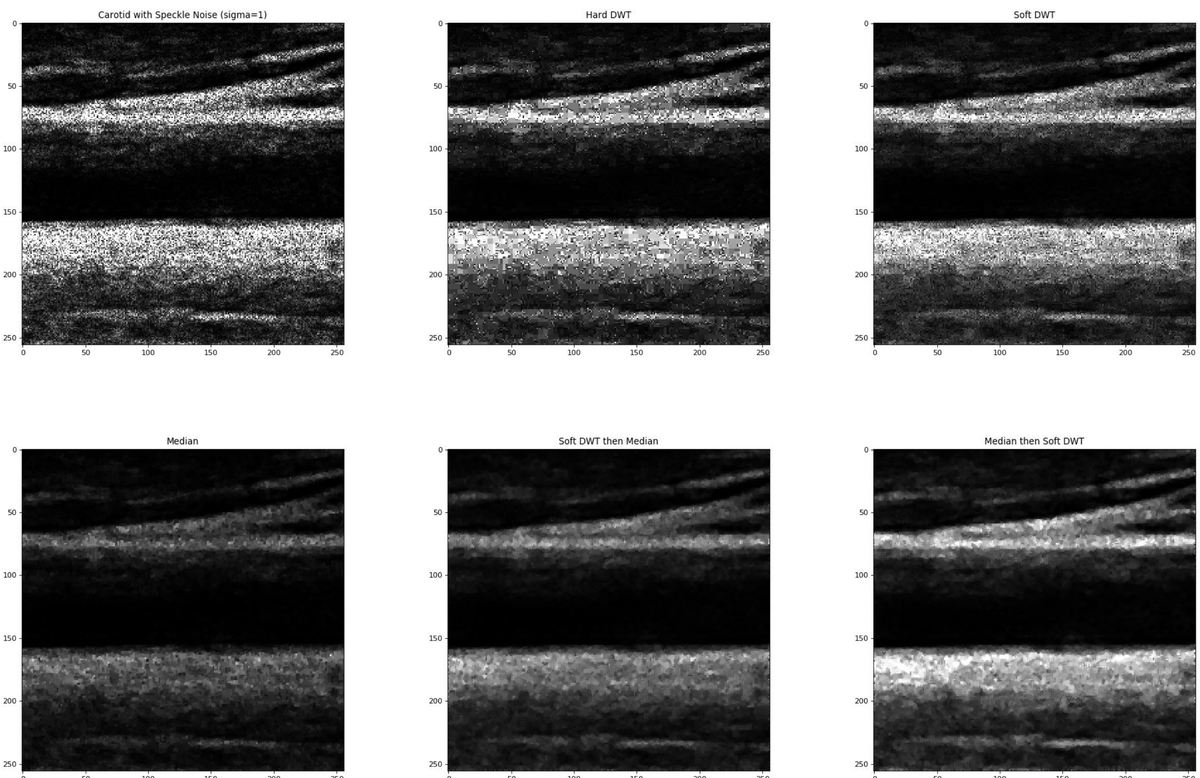


Figure 4. Comparison of filtering methods with sigma = 1 of speckle noise and optimized DWT threshold of 0.4.

It can be seen in Figure 4 that soft DWT outperformed hard DWT, but a lot of speckle noise still remained. The median filter by itself removed a lot of speckle noise, but when it was combined with the DWT, the amount of speckle noise was further reduced without over-blurring or introducing artifacts—the main features of the image are all still clear. It is important to note that use of the median filter reduces the theoretical resolution because it does blur out some texture and small details. The combination median and DWT filters also did the best job at reducing RMSE between the original and noisy image (Figure 3). The combination filters produced different results depending on the order in which the soft DWT filter and median filter were applied, as expected. They had similar successes in reducing RMSE but it appears that the median filter followed by the soft DWT produces a higher contrast image. This may be because the median filter tends to push high intensity pixels down, and processing the image with the median filter last caused a decrease in brightness in the image thus reducing the overall brightness and contrast in the image.

The main concern of using nonlinear filters like the median filter is the computation power. The median filter is computationally heavy, causing it to be much slower than other filtering methods, and especially linear filters that can be implemented with the Fourier transform. Speed is particularly important to ultrasound imaging because the images are displayed in real time, with typical frame rates of 30 fps [8] so the image must be filtered at fairly high speeds. It is possible that using more computationally expensive operations may require more expensive processors, driving up the cost or reducing the mobility of the ultrasound setup.

Conclusion

Speckle noise is a common interference pattern present in many ultrasound images due to inherent scattering of ultrasound waves in tissue. As a result, it can create undesirable effects that interfere with the clinical interpretation of medical ultrasound images. In this report, we evaluated the effectiveness of five speckle noise reduction methods: median filtering, hard DWT denoising, soft DWT denoising, and two combinations of median filtering and soft DWT denoising. To evaluate the methods, we considered a significant reduction in the RMSE of the image with less granularity and minimized block artifacts as successful. Median filtering reduced RMSE levels but tended to blur textural information that could be important to a proper clinical interpretation of the image. DWT denoising using soft thresholding performed better than hard thresholding at reducing the RMSE without blurring the image too much as long as a good threshold is chosen. While the RMSE of the DWT filtered images was reduced in comparison to the noisy image, both stand-alone DWT denoising algorithms left behind a significant amount of speckling. The combination of median filtering and soft DWT denoising were also shown to be effective methods of de-speckling ultrasound images, producing a further reduction in RMSE than the median filter or wavelet filter alone while still retaining details. The main issue we foresee in employing a median filter approach is computation power, since ultrasound involves rapid generation of many images to be seen in real time. Another issue with median filter is a decrease in resolution due to blurring. Further research to reduce noise in ultrasound images has the potential to improve interpretation and diagnosis via ultrasound.

References

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