

An Object-Based Tool for Wavelet Thresholding to Reduce Speckle Noise

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Abstract—Today, ultrasonic imaging is widely used to view the human body. Unfortunately, the presence of speckle noise decreases the quality of these images. The wavelet filtering technique is an effective method to eliminate speckle noise. In this technique, the values of the wavelet coefficients are changed according to the calculated threshold value to reduce speckle and increase image quality. Factors such as the thresholding value, thresholding method, wavelet type, level affect the success of the wavelet filtering. Thus the implementation of wavelet filtering is very important for the ultrasound image quality. In this paper, we form an object-based tool for wavelet thresholding to reduce speckle noise. Waterfall model is used for the formed tool. This tool permits applying both conventional and new wavelet filtering techniques.

Index Terms—wavelet thresholding, image denoising, speckle noise, waterfall model

I. INTRODUCTION

Ultrasonography is one of the medical imaging techniques, it is widely used to view the human body. Although, it has a lot of advantages such as low cost, portability, safety and real-time imaging [1], poor image quality is an important disadvantage for ultrasonic imaging. The ultrasound image is affected by speckle noise like other types of coherent imagery such as synthetic aperture radar and laser-illuminated imagery [2]. Speckle noise reduces the image contrast, blurs image details and decreases lesion detectability by eight-fold, thus reduces the operators ability to resolve normal and pathological tissue and complicates post-processing [3]-[5]. As for image quality, removing speckle noise in the image is very important. Wavelet filtering technique is an effective filtering technique to remove speckle noise, because wavelet coefficients have speckle information. Generally, for denoising, after calculating discrete wavelet transform (DWT), the wavelet coefficients are passed through threshold testing. Then, the resulting coefficients are used to reconstruct the signal. Over the years, many wavelet filtering techniques have been developed to obtain the optimum threshold and

thresholding methods [6]-[10]. The future works to obtain the optimum threshold for the removal of speckle noise [11]. Thus understanding the wavelet filtering is very important for ultrasound imaging. In this paper, an object-based tool is formed for the wavelet thresholding to reduce speckle noise. This application is carried out in a powerful MATLAB environment. The waterfall model is the most widely used in software development [12] and most famous software development process model [13]. Our overall requirements are known upfront and we especially like that the formed tool is easy to understand and easy to use from beginners to expert users for wavelet filters to reduce speckle noise. Thus we selected the waterfall model for planning and management of the formed tool. This model is easy to understand and implement [14]. When a new threshold is created for wavelet filtering to reduce speckle, this tool can be used because it permits the application of both conventional and new wavelet filtering techniques.

II. OBJECT-BASED TOOL FOR WAVELET THRESHOLDING

The method of wavelet thresholding removes speckle noise in the wavelet domain, where wavelet coefficients are thresholded by comparing it against the threshold. This method involves three steps: 1) Calculate DWT; 2) Process the wavelet coefficients; 3) Compute IDWT. Fig. 1 shows DWT of an image [15].

In Fig. 1, the image is decomposed into four lower resolution components; LL (approximation coefficients), LH (horizontal detail coefficients), HL (vertical detail coefficients) and HH (diagonal detail coefficients). The $g(n)$, $h(n)$ and “down arrow” in Fig. 1 mean low pass decomposition filter, high pass decomposition filter and downsampling by 2, respectively. The wavelet coefficients are determined by the following equations:

$$LL=g(n)*[g(n)*Image]_{n=2k,k \geq 0} \Big|_{n=2k,k \geq 0} \quad (1)$$

$$LH=h(n)*[g(n)*Image]_{n=2k,k \geq 0} \Big|_{n=2k,k \geq 0} \quad (2)$$

$$HL=g(n)*[h(n)*Image]_{n=2k,k \geq 0} \Big|_{n=2k,k \geq 0} \quad (3)$$

$$HH=h(n)*[h(n)*Image]_{n=2k,k \geq 0} \Big|_{n=2k,k \geq 0} \quad (4)$$

where * denotes convolution.

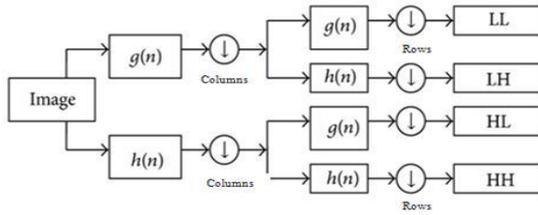


Figure 1. DWT decomposition of an image.

After calculating the DWT, to process the wavelet coefficients, a threshold operator is used. There are two types of thresholding methods, hard thresholding and soft thresholding.

Hard thresholding:

$$ht(x) = \begin{cases} 0, & |x| < T \\ x, & |x| \geq T \end{cases} \quad (5)$$

Soft thresholding:

$$st(x) = \begin{cases} 0, & |x| < T \\ \text{sign}(x) \cdot (|x| - T), & |x| \geq T \end{cases} \quad (6)$$

where x is the image and T is the threshold value. To find the threshold value in (5) and (6), different rules were proposed in the literature [6]-[9]. After processing the wavelet coefficients with the thresholding method, the resulting coefficients are used to reconstruct the signal.

The formed tool for wavelet thresholding is shown in Fig. 2.

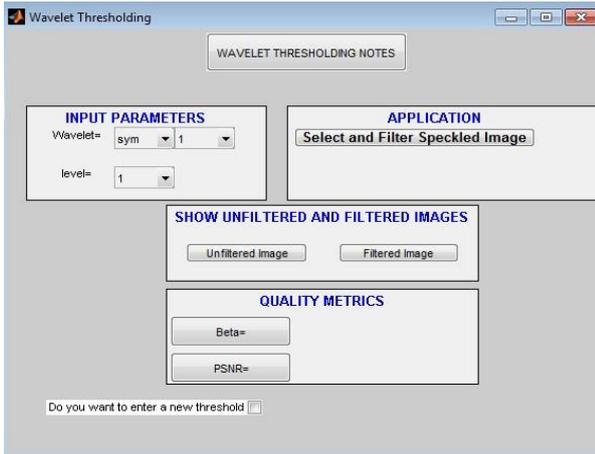


Figure 2. Formed tool for wavelet thresholding.

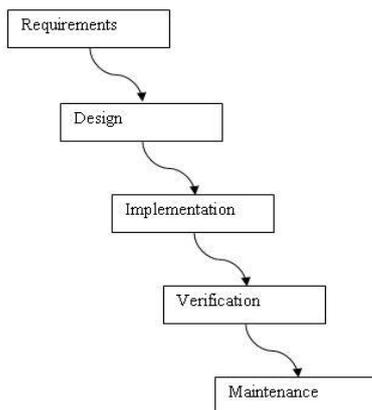


Figure 3. The waterfall model.

According to the above-mentioned wavelet thresholding method, this tool filters speckled image. The waterfall model was used for the formed tool. This model has five stages of requirements, design, implementation, verification and maintenance. As shown in Fig. 3, the waterfall model maintains that one should move to a stage only after its preceding stage is reviewed [16].

The stage of requirements in the waterfall model is the first part of the formed tool. This part contains choosing the “wavelet type” and “level” to improve the output image quality (Fig. 4a). There are different wavelets such as sym, db, coif and one of them gives an output image with a different quality. After the speckled image is decomposed, only detail coefficients are passed through a thresholding testing. Then, we need to increase the number of levels to improve the output image quality. The LL subband can further be decomposed to obtain another level of decomposition (mentioned in the “wavelet thresholding notes” shown in Fig. 4b).



Figure 4. (a) Input parameters (b) wavelet thresholding notes

The stages of design and implementation in the waterfall model are the second part of the formed tool. With regard to image denoising, employed functions of the wavelet toolbox in the MATLAB include dwt2 (single-level discrete 2-D wavelet transform with the selected mother function), idwt2 (inverse transform that gives the final denoised image) and wthresh (thresholding of the input image). After the implementation of filtering, the formed tool allows the filtered and unfiltered images to be displayed.

The stages of verification and maintenance in the waterfall model are the last part of the formed tool. With regard to the computation of performance indexes, beta [17] and PSNR (Peak Signal-to-Noise Ratio) metrics are used in the formed tool. Beta is used to evaluate edge preservation in the filtered image and defined by:

$$\beta = \frac{\Gamma(\Delta I - \bar{\Delta I}, \Delta \hat{I} - \bar{\Delta \hat{I}})}{\sqrt{\Gamma(\Delta I - \bar{\Delta I}, \Delta I - \bar{\Delta I}) \cdot \Gamma(\Delta \hat{I} - \bar{\Delta \hat{I}}, \Delta \hat{I} - \bar{\Delta \hat{I}})}} \quad (7)$$

$$\Gamma(I_1, I_2) = \sum_{(i,j) \in ROI} I_1(i,j) \cdot I_2(i,j)$$

where ΔI and $\Delta \hat{I}$ represent the high pass filtered version of the original image $I(i,j)$ and its denoising version $\hat{I}(i,j)$, obtained with 3×3 -pixels standard approximation of Laplacian operator. $\bar{\Delta I}$ and $\bar{\Delta \hat{I}}$ are the mean intensities of ΔI and $\Delta \hat{I}$, respectively.

Another metric is PSNR:

$$PSNR = 10 \cdot \log_{10} \left(\frac{L^2}{n \cdot m} \sum_{i=1}^n \sum_{j=1}^m [I_{ref}(i,j) - I_f(i,j)]^2 \right) \quad (8)$$

where I_{ref} is the reference image, I_f is the noisy or filtered image, $n \cdot m$ is the image size, L is the maximum possible pixel value of the image.

The default threshold for the tool is universal threshold, proposed by Donoho [6]. The formed tool allows filtering

of the speckled image with a new threshold. Thus, the effect of a different threshold can be tested to improve image quality.

III. RESULTS AND DISCUSSION

The formed tool is easy to understand and easy to use due to the waterfall method. Anyone who wants to filter a speckled image with a wavelet filter to reduce speckle noise can use this tool easily. The waterfall method contains all stages the formed tool needs.

At first, we used the Lena image to test the formed tool. The MATLAB Image Processing Toolbox (IPT) function, `imnoise`, was used to add speckle noise.

To filter the speckled image with the formed tool, first of all, the wavelet type and level was selected (we selected `sym 5` as the wavelet type and level 2 to filter the speckled Lena image). After the speckled image is selected, the filtering is carried out with the “filter speckled image” module. After filtering the noisy Lena image, the formed tool is shown in Fig. 5. The filtered image is saved automatically.

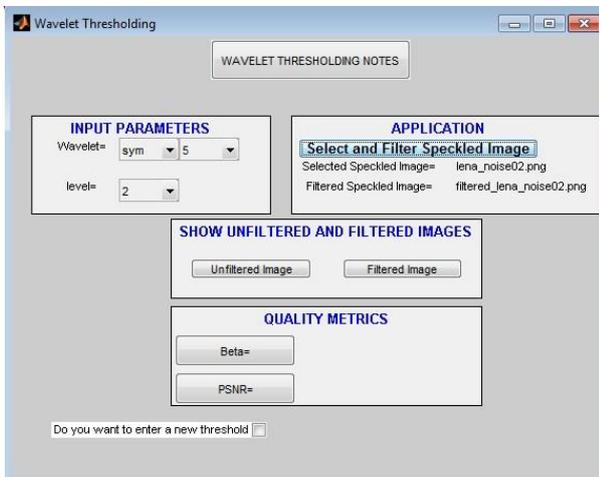


Figure 5. After filtering (wavelet type is `sym5` and level 2), the formed tool.

For a qualitative comparison, after the filtering, “show unfiltered and filtered images” module is used. Fig. 6 shows unfiltered and filtered Lena images. For a quantitative comparison, the “beta” and “PSNR” modules were used. Fig. 7 shows the beta and PSNR values after filtering.

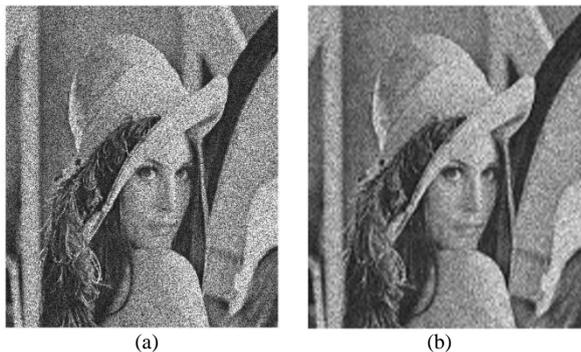


Figure 6. (a) Noisy Lena image (b) filtered Lena image (wavelet type is `sym5` and level 2).

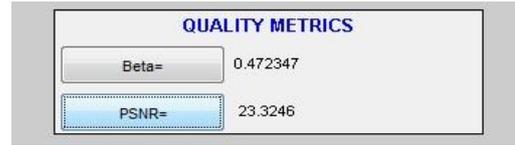


Figure 7. Beta and PSNR values (wavelet type is `sym5` and level 2).

If we use level 1 instead of level 2 for the same noisy Lena image, the filtered Lena image and the resulting tool are shown in Fig. 8 and Fig. 9, respectively. If comparing Fig. 6b and Fig. 8, Fig. 6b is a more refined filtered image than Fig. 8. As we can see by comparing Fig. 6b and Fig. 8, the filtered Lena image with level 2 has greater beta and PSNR values than that of the filtered Lena image with level 1. These results show that if the wavelet type is `sym5`, the wavelet thresholding with level 2 is more effective than the wavelet thresholding with level 1 for the noisy Lena image.



Figure 8. Filtered Lena image (wavelet type is `sym5` and level 1)

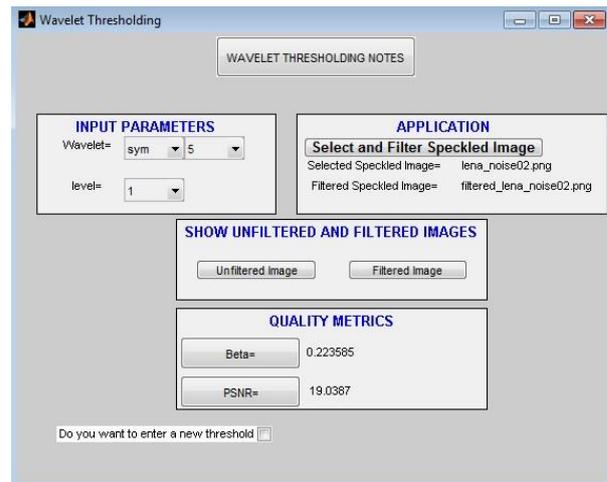


Figure 9. After filtering (wavelet type is `sym5` and level 1), the formed tool.

If “do you want to enter a new threshold” module is used, the formed tool filters the speckled image with threshold which the user enters. The default threshold value for the formed tool is universal threshold. If a new threshold is created, the tool uses the created threshold due to this module. We used a random threshold, whose value is 0.1, to filter the noisy Lena image with parameters: wavelet type = `db8`, level = 5. After filtering, the formed tool and the filtered Lena image are shown in Fig. 10 and Fig. 11, respectively.

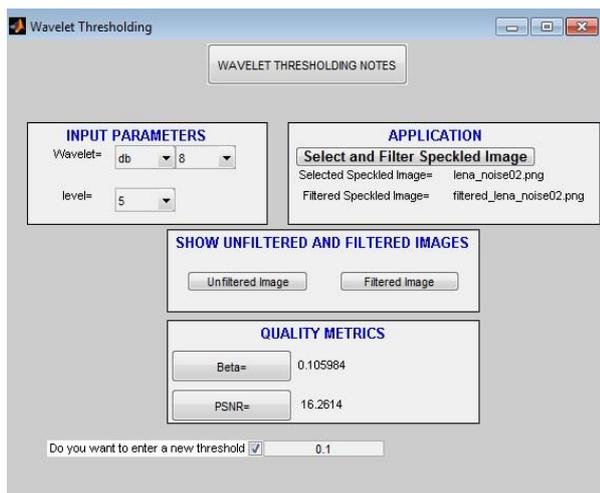


Figure 10. After filtering (wavelet type is db8, level 5), the formed tool.



Figure 11. Filtered Lena image (wavelet type is db8, level 5).

Due to the formed tool, we tested the wavelet filtering with various thresholding values. In this application the wavelet type, level and threshold value are selected randomly. If comparing Fig. 11 with Fig. 6b and Fig. 8, Fig. 11 is the worst filtered image among these images. This is likely because, the selected low threshold value. It is possible to test any created threshold value for wavelet thresholding due to the formed tool.

The second type of image we used in our study was the kidney image which was obtained from the AnatQuest library (<http://anatquest.nlm.nih.gov>). We used Field II software [18], [19] to produce the noisy kidney image from this kidney image. After filtering the noisy kidney image, generated by Field II, with the formed tool, the noisy and filtered kidney image are shown in Fig. 12.

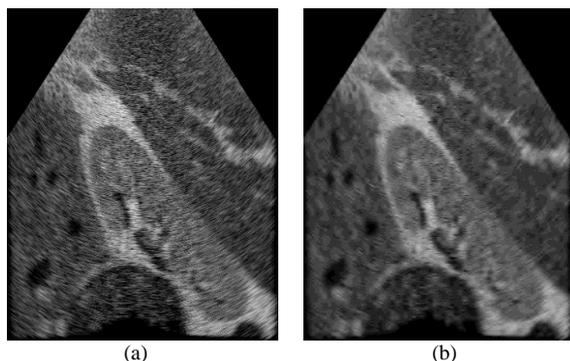


Figure 12. (a) Noisy kidney image, generated by Field II (b) filtered kidney image with the formed tool.

IV. CONCLUSION

In this study we formed an object-based tool to reduce speckle noise by using wavelet thresholding. The waterfall model was used for this tool. Due to the waterfall model, this formed tool is easy to understand and easy to use even for beginners who want to filter speckled image with wavelet filters. We tested the formed tool with the kidney image that is simulated by the Field II program and the Lena image. At first we selected the wavelet type and level, later speckled image was filtered. After filtering, both the filtered and unfiltered images were shown on display for a qualitative comparison and the quality of the images have been evaluated using beta and PSNR metrics by using the formed tool. Additionally, the formed tool allows any threshold value to filter speckled image with a wavelet filter. By using this tool, anyone can easily perform both the conventional and new wavelet filtering techniques to reduce speckle noise. The formed tool assures good performance to filter the speckled image with wavelet filter and as such we recommend it as a useful tool.

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