inverse problems. Wiener filter provides the best restored signal with respect to the square error averaged over the original signal and the nois e among linear operators. Based on Wiener filter method, F. Jin et al. considered the adaptive Wiener filtering of noisy images and image sequences. An adaptive weighted averaging approach was used to estimate the second-order statistics required by the Wiener filter. From the experiment, it shows that the result from Wiener filter has improved the peak-to-peak signal noise ratio (PSNR) by about 1dB. It has also improved the annoying boundary noise significantly [11-13].

2. Methods and Materials

This was experimental work carried out to enhance the quality of ultrasound images of long bone fracture through removal of speckle noise using techniques such as Median, Average and Wiener Filtering. The median filter is a non-linear digital filtering technique; it used to remove noise from images. It is useful to reduce speckle noise and salt and pepper noise. Its edge-preserving nature makes it practical in cases where edge blurring is undesirable. Average Filter performs spatial filtering on each individual pixel in an image using the grey level values in a square or rectangular window surrounding each pixel.

Image analysis using MatLab:
1. Top-hat filtering.
IM2 = imtophat (IM, SE) performs morphological top-hat filtering on the grayscale or binary input image IM. Top-hat filtering computes the morphological opening of the image (using imopen) and then subtracts the result from the original image. Imtophat uses the structuring element SE, where SE is returned by strel. SE must be a single structuring element object, not an array containing multiple structuring element objects. IM2 = imtophat (IM, NHOOD) where NHOOD is an array of 0s and 1s that specifies the size and shape of the structuring element, is the same as imptophat (IM, strel (NHOOD)).

2. Deblurring Images Using the Blind Deconvolution Algorithm
The Blind Deconvolution Algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The algorithm restores the image and the point-spread function (PSF) simultaneously. The accelerated, damped Richardson-Lucy algorithm is used in each iteration. Additional optical system (e.g. camera) characteristics can be used as input parameters that could help to improve the quality of the image restoration. PSF constraints can be passed in through a user-specified function.
The steps of Blind Deconvolution Algorithm
Step 1: Image Reading
Step 2: A Blur Simulation
Step 3: The Blurred Image Using PSFs of Various Sizes Restoration
Step 4: The Restored PSF Analysis
Step 5: The Restoration Improvement
Step 6: Using Additional Constraints on the PSF Restoration

3. The Results

Ultrasound images in general are complex due to data composition, which can be described in terms of speckle information. Upon visual inspection, speckle noise consists of a relatively high grey level intensity, qualitatively ranging between hyperechoic (bright) and hypoechoic (dark) domains. In addition, ultrasound images have the advantage of being non-invasive, portable, versatile, and low cost and not requiring ionizing radiations. Therefore, those images need to be modified by using image processing program to get rid the noise, blurring and unwanted information. The main objective of this study was to study the enhancement of ultrasound image using filtering technique.

1. Top-hat filtering
It performed morphological top-hat filtering on the grayscale or binary input image IM figure 1 and figure 3-2.

Figure 1: Original Ultrasound image

Figure 2: Enhanced Ultrasound using Top-hat filtering

2. Deblurring Images Using the Blind Deconvolution Algorithm
The Blind Deconvolution Algorithm can be used effectively when no information about the distortion (blurring and noise) is known. The algorithm restores the image and the point-spread function (PSF) simultaneously. The accelerated, damped Richardson-Lucy algorithm is used in each iteration. Additional optical system (e.g. camera) characteristics can be used as input parameters that could help to improve the quality of the image restoration. PSF constraints can be passed in through a user-specified function.

Step 1: Image Reading
The example reads in an intensity image. The deconvblind function can handle arrays of any dimension figure 3.

Figure 3: Original Ultrasound image

Step 2: A Blur Simulation

Simulate a real-life image that could be blurred (e.g., due to camera motion or lack of focus). The example simulates the blur by convolving a Gaussian filter with the true image (using imfilter). The Gaussian filter then represents a point-spread function, PSF figure 4.

Figure 4: A blurred U/S image

Step 3: The Blurred Image Using PSFs of Various Sizes Restoration

To illustrate the importance of knowing the size of the true PSF, this example performs three restorations. Each time the PSF reconstruction starts from a uniform array--an array of ones. The first restoration, J1 and P1, uses an undersized array, UNDERPSF, for an initial guess of the PSF. The size of the UNDERPSF array is 4 pixels shorter in each dimension than the true PSF figure 5.

Figure 5: A blurred U/S image using Undersized PSF

The second restoration, J2 and P2, uses an array of ones, OVERPSF, for an initial PSF that is 4 pixels longer in each dimension than the true PSF figure 6.

Figure 6: Deblurring with Oversized PSF for U/S image

The third restoration, J3 and P3, uses an array of ones, INITPSF, for an initial PSF that is exactly of the same size as the true PSF figure 7.

Figure 7: Shows Deblurring with INITPSF for U/S image

Step 4: The Restored PSF Analysis

All three restorations also produce a PSF. The following pictures show how the analysis of the reconstructed PSF might help in guessing the right size for the initial PSF. In the true PSF, a Gaussian filter, the maximum values are at the center (white) and diminish at the borders (black) figure 8.

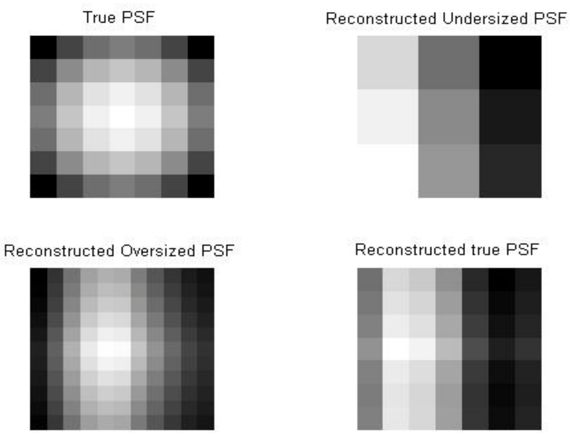

Figure 8: The restored PSF for U/S image Analyzing

The PSF reconstructed in the first restoration, P1, obviously does not fit into the constrained size. It has a strong signal variation at the borders. The corresponding image, J1, does not show any improved clarity vs. the blurred image, Blurred. The PSF reconstructed in the second restoration, P2, becomes very smooth at the edges. This implies that the restoration can handle a PSF of a smaller size. The corresponding image, J2, shows some deblurring but it is strongly corrupted by the ringing. Finally, the PSF reconstructed in the third restoration, P3, is somewhat intermediate between P1 and P2. The array, P3, resembles the true PSF very well. The corresponding image, J3, shows significant improvement; however it is still corrupted by the ringing.

Step 5: Improving the Restoration
The ringing in the restored image, J3, occurs along the areas of sharp intensity contrast in the image and along the image borders. This example shows how to reduce the ringing effect by specifying a weighting function. The algorithm weights each pixel according to the WEIGHT array while restoring the image and the PSF. In our example, we start by finding the "sharp" pixels using the edge function. By trial and error, we determine that a desirable threshold level is 0.3 figure 9. To widen the area, we use imdilate and pass in a structuring element, se.

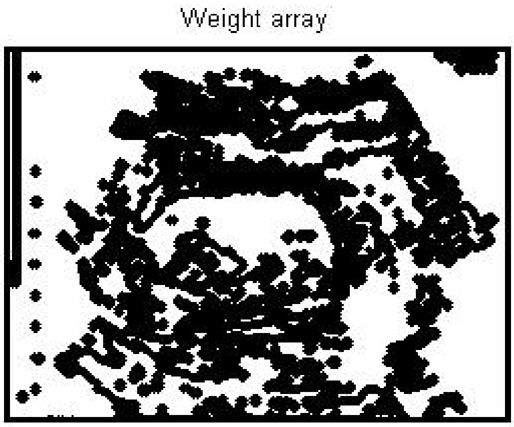

Figure 9: The Restoration of U/S image improvement

Step 6: Using Additional Constraints on the PSF Restoration
The function, FUN, below returns a modified PSF array which deconvblind uses for the next iteration. In this example, FUN modifies the PSF by cropping it by P1 and P2 number of pixels in each dimension, and then padding the array back to its original size with zeros. This operation does not change the values in the center of the PSF, but effectively reduces the PSF size by 2*P1 and 2*P2 pixels as shown in figure 10.

Figure 10. The deblurred Image

The anonymous function, FUN, is passed into deconvblind last. In this example, the size of the initial PSF, OVERPSF, is 4 pixels larger than the true PSF. Setting P1=2 and P2=2 as parameters in FUN effectively makes the valuable space in OVERPSF the same size as the true PSF. Therefore, the outcome, JF and PF, is similar to the result of deconvolution with the right sized PSF and no FUN call, J and P, from step 4 as shown in figure 11.

Figure 11: Anonymous function of Deblurred Image

If the oversized initial PSF, OVERPSF, had used without the constraining function, FUN, the resulting image would be similar to the unsatisfactory result, J2, achieved in Step 3 as shown in figure 11.

4. Conclusion

Ultrasound images in general are complex due to data composition, which can be described in terms of speckle information. Upon visual inspection, speckle noise consists of a relatively high grey level intensity, qualitatively ranging between hyperechoic (bright) and hypoechoic (dark) domains. In addition, ultrasound images have the advantage of being non-invasive, portable, versatile, and low cost and not requiring ionizing radiations. Therefore, those images need to be modified by using image processing program to get rid the noise, blurring and unwanted information .This was an experimental study to study the enhancement of ultrasound image using filtering technique using image processing technique (MatLab version R2009a). In addition to evaluate contrast enhancement pattern in different ultrasound images such as grey color in order to evaluate the usage of new nonlinear approach for contrast enhancement of soft tissues in panoramic images. The main techniques of enhancement used in this study was Top-hat filtering which computed the morphological opening of the image (using imopen) and then subtracts the result from the original image. The anther technique was Deblurring Images Using the Blind Deconvolution Algorithm which can be used effectively when no information about the distortion (blurring and noise) is known. The results of this study were agreed with previous studies in blind Deconvolution algorithm and it added new approach by using both technique in U/S image processing which would increase the diagnostic value of those images. So conclusion of this research that the new approach is funded on an attempt to interpret the problem from the view of blind source separation (BSS), thus to see the U/S image as a simple mixture of (unwanted) background information, diagnostic information and noise and filtered it. The detection of the noise is a complex procedure which is difficult to detect by naked eye so that image analysis should be performed by using powerful image processing.

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