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COMPARISON OF DENOISING METHODS FOR DIGITAL MAMMOGRAPHIC IMAGE

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Abstract. We compared effects of denoising methods on digital mammographic images. The denoising methods studied were an adaptive Wiener filter and low-pass Gaussian filter. The denoising methods were applied as an image preprocessing techniques before enhancement. The performance of image denoising methods are based on Mean Squared Error (MSE) and Peak Signal To Ratio (PSNR) values.

Keywords: Adaptive Wiener filter; Low-pass Gaussian filter; Mean Squared Error (MSE); Peak Signal to Noise Ratio (PSNR)

Abstrak. Kami membandingkan kaedah untuk membuang hingar dari imej mamografi digital. Kaedah yang dikaji adalah penuras Wiener suai padan dan penuras Gauss lepas rendah. Kaedah ini diaplikasikan dalam teknik pra pemprosesan imej sebelum proses penambahbaikan imej. Pencapaian untuk kedua-dua kaedah membuang hingar dari imej dinilai melalui min ralat kuasa dua dan nisbah isyarat-hingar puncak.

Kata kunci: Penuras Wiener suai padan; Penuras Gauss lepas rendah; Min ralat kuasa dua; Nisbah isyarat-hingar puncak

1.0 INTRODUCTION

The breast cancer is the most common form of cancer in female population and continues to be leading cause of death among women around the world. Mammography images are difficult to interpret by the radiologist because the features are typically very small and have a wide range of anatomical patterns.

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The quality of images also depends on the physical properties of the radiographic images such as contrast, resolution and noise [1]. The noise in digital mammographic image and low contrast regions give negative effect to correct diagnosis.

For digital mammography system, noise can result from flat-fielding, detector gain variations, electronic noise of the detectors and the analog to digital conversion system [2]. Suitable denoising method should be developed to achieve the appropriate SNR value to allow perception of lesions. Image preprocessing is an important procedure to reduce the noise level of the image preserving the mammography structures and to improve the detection of mammography features.

Past studies have been devoted to denoise the mammographic images while other studies were concerned with contrast enhancement. In dense regions of breast, the pixel intensity increases with the increase of noise and this cause difficulties to localize the details [3]. Wavelet shrinkage from second level to forth level decomposition are used as image denoising method for different noise variance [3]. Adaptive filter using 1D LMS algorithms which is applied in signal processing could be used as a denoising method for mammography images [4].

Based on a local contrast modification function [5], computer simulated images gave better SNR value compared to the real phantom images. Donoho [6] studied wavelet shrinkage based on the wavelet decomposition of the image. However to obtain the denoised signal for two dimensional image, the inverse wavelet transform was applied in the last step of denoising algorithms. The three denoising methods namely a local Wiener filter, a filter based on soft thresholding of the wavelet transform coefficients and Independent Component Analysis (ICA) filter were compared based on the Mean Squared Error (MSE) value.

In this paper, the denoising methods using an adaptive Wiener filter and low pass Gaussian filter were evaluated on computer simulated images and on the mammographic images. The methods were chosen as an image pre-processing techniques because both methods required few parameter adjustments. The performances of image denoising methods were compared based on the Mean Squared Error (MSE) and the Peak Signal To Noise Ratio (PSNR) value.

2.0 METHODS DESCRIPTION

2.1 An Adaptive Wiener Filter

An adaptive 2D Wiener filtering was performed on grayscale images. A local neighborhood at each pixel was estimated statistically. This low pass filter was applied in a local neighborhood of 3 × 3 pixels blocks of the image. An adaptive Wiener estimated the local mean and variance around each pixel as follows [7]:

$$\mu = \frac{1}{NM} \sum_{n_1 n_2 \in \eta} a(n_1, n_2) \tag{1}$$

and

$$\sigma^2 = \frac{1}{NM} \sum_{n_1 n_2 \in \eta} a^2(n_1, n_2) - \mu^2 \tag{2}$$

where η is the N by M local neighborhood of each pixel in the image and

$$b(n_1,n_2) = \mu + \frac{\sigma^2 - \nu^2}{\sigma^2}(a(n_1,n_2) - \mu) \tag{3}$$

where ν^2 is the noise variance.

2.2 Low Pass Gaussian Filter

Many types of noise can be removed by Gaussian filter. In two dimensions, it is the product of the two Gaussians, one per direction [8],

$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{\frac{-x^2 + y^2}{2\sigma^2}} \tag{4}$$

where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis and σ is the standard deviation of the Gaussian distribution. The standard deviation, σ of the addictive white Gaussian noise was set to 0.6. The estimated parameter σ = 0.6 was applied to the real mammographic images and simulated image.

This filtering method involved convolution. The formula for two dimensional convolution matrix was precomputed and convolved with two dimensional data. This filter affected the image blur which was called Gaussian blur. Each element in the matrix represented a pixel attribute such as brightness or colour intensity in image pre-processing techniques.

2.3 Measuring Image Quality

Peak signal to noise ratio (PSNR) and Mean Squared Error (MSE) of the output image were measured in order to compare the two noise reduction techniques [9]. The MSE is [9],

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left|x(i,j)-y(i,j)\right|^2}{MN} \tag{5}$$

where $x(i,j)$ is the original image, $y(i,j)$ is the output image, and MN is the size of the image.
The PSNR is [9],

$$PSNR = 20\log_{10}\left[\left(\frac{2^{\eta}-1}{\sqrt{MSE}}\right)\right] \quad \text{dB} \tag{6}$$

3.0 COMPUTER SIMULATED AND REAL MAMMOGRAPHIC IMAGES

3.1 Computer Simulated Images

Computer simulated images which contain a nodule similar to the mammographic image were generated. Only one nodule image was studied because it was easy to generate. Poisson noise was later added to the image.

The nodule of simulated image was chosen to reduce the number of evaluation. The image was 256 × 256 pixels for nodule and was coded on 256 gray levels. Figure 1 shows an example of computer simulated image of a nodule, and Figure 2 is the image with Poisson noise added.

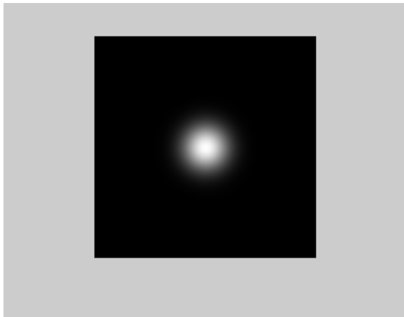

Figure 1 Original computer simulated nodule

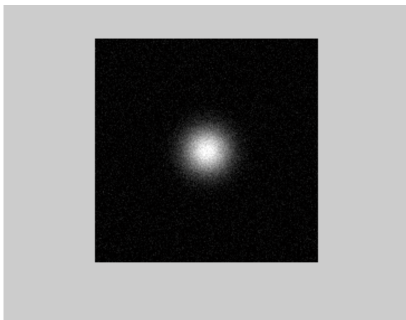

Figure 2 Computer simulated nodule added with Poisson noise

3.2 Real Digital Mammographic Images

The digital mammographic images were selected from MedPix medical image database system provided by the Department of Radiology and Biomedical Informatics, Uniformed Services University, USA. This original image from the database was corrupted by Poisson noise. The images were digitized with the size of 1024 × 1024.

Both computer simulated image and real digital mammographic image were subjected to the 2D Wiener filter and low pass Gaussian filter. The MSE and PSNR were calculated for images before and after the applications of the denoising methods.

4.0 RESULT AND DISCUSSION

The 2D Wiener filter and low pass Gaussian filter were applied on both computer simulated image and images from database. The comparison among the denoising methods results were quantitatively measured by using Mean Squared Error (MSE) and Peak Signal To Ratio (PSNR) values.

Table 1 shows the results of denoising methods according to MSE and PSNR obtained from three different images selected from image database.

Table 1 Comparison of 2D Wiener filter and low pass Gaussian filter

	Image	2D Wiener Filter	Low Pass Gaussian filter
MSE	Nodule Simulated Image	7.7111e - 007	0.0155
	<u>Real Mammographic Image</u>		
	Image 1	0.6111	0.0329
	Image 2	0.6459	0.0436
PSNR (dB)	Nodule Simulated Image	85.1984	42.1613
	<u>Real Mammographic Image</u>		
	Image 1	26.2046	38.8892
	Image 2	25.9641	37.6674

4.1 Two Dimensional Wiener Filter

Figure 3(a) shows the original mammographic image, and Figure 3(b) is the best result after applying 2D Wiener filter.

Figure 3 (a) Original mammographic image

Figure 3 (b) 2D Wiener filtered image

4.2 Low Pass Gaussian Filter

Figure 4(a) shows original mammographic image, and Figure 4(b) is the best result after applying low pass Gaussian filter.

Figure 4 (a) Original mammographic image

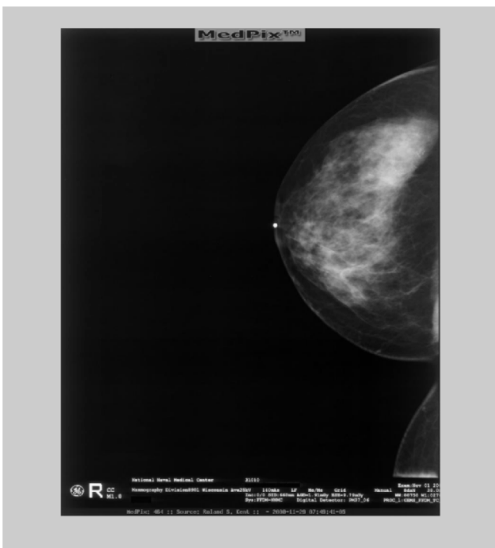

Figure 4 (b) Low pass Gaussian filtered image

Figure 5 and 6 show the comparison between the denoising methods. PSNR values were plotted versus MSE parameter. The curves show that the PSNR values increased with the decreasing MSE parameters.

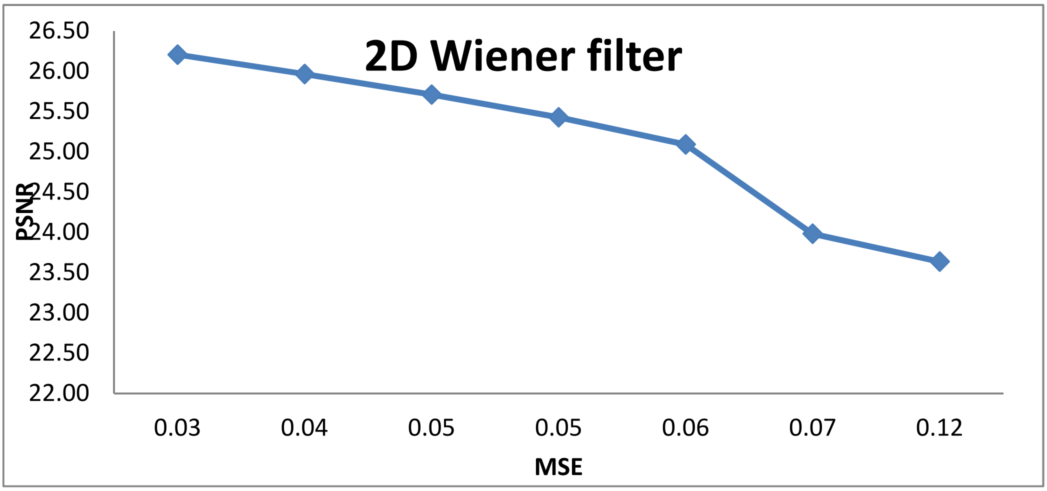

Figure 5 PSNR values decrease with the increasing MSE parameter for Wiener2 filter

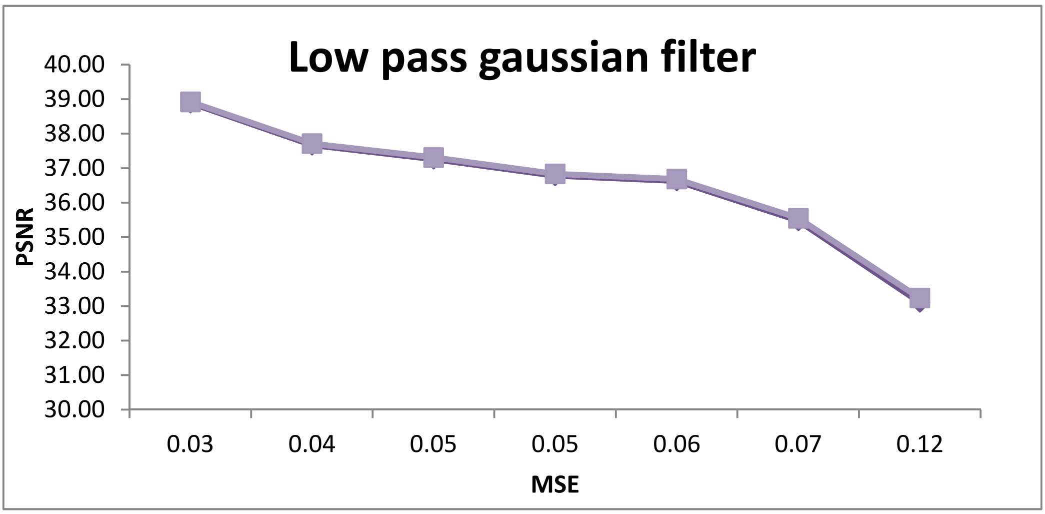

Figure 6 PSNR values decrease with the increasing MSE parameter for low pass Gaussian filter

However, the MSE value was not related with the denoising visual results. The purpose of creating nodule simulated image was to investigate the operation and robustness of algorithms for denoising methods. The results showed that low pass Gaussian filter gave better results compared to 2D Wiener filter for the real mammographic images. Low pass Gaussian filter worked well in the real mammographic images because the images were corrupted by addictive white Gaussian noise. The results for nodule simulated image had little value in assessing or developing the algorithms.

5.0 CONCLUSION

We conclude that low pass Gaussian filter was better than 2D Wiener filter for preprocessing of images.

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