Despeckling of Ultrasonogram using Weiner Filter Exploiting Patch Redundancy

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***Abstract* – Ultrasonograms are ultrasound medical images. Even if there are multiple modalities of medical image acquisition, Ultrasonogram is mostly used because it is non-invasive, practically harmless to human body, portable, accurate, has low acquisition cost and has the capability of forming real time imaging. However, the presence of noise components is more on Ultrasound image compared to other costlier methods like CT and MRI. The great challenge of Ultrasound Medical image denoising is to preserve the edges and all fine details of an image when reducing the noise. Many denoising techniques have been proposed for effective suppression of speckle noise in ultrasound images. Here a detailed survey of different techniques for ultrasound image denoising is done. From the survey it is analysed that, recently filtering in spatial domain has deeply evolved due to the introduction of patches. For removing speckle noise from ultrasound images patch-based filters give some of the best results among other powerful methods such as wavelet based approaches or diffusion techniques. In this paper a Weiner filter exploiting patch redundancy is used to denoise ultrasound images. SinceWeiner filter is itself a minimum mean squared error filter (MMSE), the proposed ultrasound image denoising leads to near optimal performance in MSE sense.**

Keywords – Ultrasonogram; Weiner Filter; Patch based Denoising; Ultrasound; Despeckling;

I. INTRODUCTION

Medical Ultrasound imaging has been used for effective diagnostics of diseases over the past decades. It is done using ultrasonic waves in 3 to 20 MHz range. Ultrasound waves produced from the transducer travel through body tissues and on reaching an object or surface with different texture or acoustic nature, the wave gets reflected back. These echoes are captured by the apparatus (the transducer array) and converted into electric current, which is amplified and conditioned and shown on a display device in real time. The image generated by Ultrasound Scanning is called an Ultrasonogram. The resolution of the image will be better by using higher frequencies but this at the same time limits the depth of the penetration. There exist different modes of ultrasound imaging, among which the most common modes are [1]:

- b-mode or brightness mode: the basic two-dimensional intensity mode,
- m-mode: to assess moving body parts (e.g:cardiac movements) from the echoed sound and
- colour mode: pseudo colouring based on the detected cell motion using Doppler analysis.

However, Ultrasound image contains more noise content compared to any other imaging modality. Major part of this noise is speckle, which is a multiplicative noise arising due to coherent wave interface. Speckle gives a granular appearance to otherwise homogeneous ultrasound images. It also reduces image contrast and detail resolution, and diminishes the ability to differentiate normal and malignant tissues within ultrasound images, thus resulting in fault diagnostics. In case of image denoising methods, the characteristics of the degrading system and the noises are assumed to be known beforehand. The denoising concept can be explained with the help of the following figure (1.1), where the image f(x,y) is blurred by a linear operation and as a result noise n(x,y) is added to form the degraded image g(x,y). This is convolved with the restoration procedure to produce the restored image z(x,y) [2].

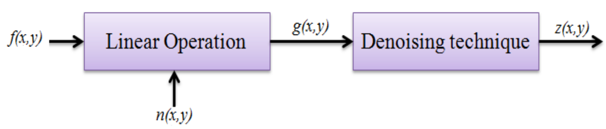

Fig. 1 : Denoising Concept.

In case of ultrasound images, the linear operation shown in Figure 1.1 is the multiplication of the noise n(x,y) to the original images f(x,y), producing corrupted image g(x,y). This can be represented as follows:

$$f(x) = g(x) .n(x) \quad (1)$$

Once the corrupted image g(x,y) is obtained, it is subjected to the denoising technique to get the denoised image z(x,y). The general requirements for ultrasound image denoising are to effectively suppress speckle noise while retaining useful details of the image for analysis and diagnosis.

The rest of the paper is organized as follows: Section II surveys the various speckle reduction techniques, followed by observation and analysis from the survey. Section III explains the proposed ultrasound image denoising. Section IV include the results and section V concludes the work.

II. DESPECKLING TECHNIQUES

Ultrasound images requires specific filter due to the signal dependant nature of speckle noise present. Several techniques have been proposed for despeckling ultrasound images. The classification and theoretical overview of existing despeckling techniques is presented in this section.

A. Localised models [3]

These models use locality assumption during modellingof image signals to overcome curse of dimensionality and have been found effective in removing wide range of noise from various imaging modalities.

1) Linear filtering [4][5]: This includes traditional image noise reduction techniques such as Wiener, Lee, Frost and Kaun filters. Lee filter forms an output from weighted average which is calculated using sub-region statistics over different pixel windows. It uses local statistics to effectively preserve edges and is computationally simple. But this filter ignores speckle noise near edges.

Kaun filter has the same form as the Lee filter but is different in its weighting function, since it makes no approximation to the original model. They are computationally simple like Lee filter but is considered to be superior toLee filter. The problem with Kaun filter is that it relies on the Equivalent Numbers of Looks (ENL) from an image to determine a different weighted function W to perform the filtering.

The Frost filter is an adaptive and exponentially weighted averaging filter based on the coefficient of variation, which is the ratio of the local standard deviation to the local mean of the degraded image. These locally based filters compromise between the averaging (in homogeneous regions) and preserving at edges and features.

Weiner filter restores the image in the presence of blur and noise. It is also known as Least Mean Square filter. In this filter smoothing of the image is performed based on the computation of local image variance. This approach produce better quality results than other linear filtering techniques, since it is adaptive. It helps in preserving edges and other high frequency information of the image. The problem with this filter is that it requires more computation time than other linear filtering techniques and it blurs the image, also it performs poorly in case of non-Gaussian noise.

2) Non Linear filtering [6]: These filters doesnt use Gaussian noise assumption as in linear filters. Simplest non linear filter is median filter, It replaces the middle pixel in the window with the median value of its neighbours. They are capable of preserving edges. But the problem is it is difficult to design. It also blur edges and tiny details.

3) Diffusion filtering [4]: These are non linear filtering techniques which include Partial Differential Equation (PDE) based approaches, where diffusion is often driven bylocal gradient calculated from image intensity values. These filters perform contrast enhancement and noise reduction without requiring the power spectrum information of the image. But these methods have limitation in retaining subtle features such as small cysts and lesions in ultrasound images. Speckle Reducing Anisotropic Diffusion filter (SRAD) is a non-linear and space-variant diffusion filter. It produces resulting images based on an iterative diffusion process. SRAD exploits the instantaneous coefficient variation for removing speckle.

4) Wavelet filtering [7]: This is a noise reduction technique in which only useful wavelet coefficients are utilized. The problems with these approaches are they use threshold in filtering process, and its inappropriate choice can lead to average filtering and noisy boundaries.

B. Non localised models [3][8]

Non local dependency arises from geometric similarity of natural objects and it is useful in medical images because of geometric constraints existing in human body. A patch based non local algorithm was proposed. It is an NLM filter which performs non local comparison of image patches using information redundancy in the image and thus helps to effectively denoise natural images highly corrupted by noise.

Various methods are found in literature to make this model adaptable to speckle and thus used in denoising ultrasound images.

C. Observation and Analysis

The various localized models for despeckling ultrasonograms use locality assumption for denoising images. They include both linear and non linear filters. Weiner filter produces better results in denoising among various linear filters but since it uses Gaussian assumption for noise it is found to be inefficient in despekling ultrasound images. So non linear filters are mostly used in ultrasound image despeckling. SRAD has best performance for despeckling among different non linear filters since it is specifically designed for removing speckles. Wavelet based filtering also produces best results in despeckling comparable with SRAD filtering. Non localised models are gaining better popularity recently since they use geometrical similarity existing in images. Many of the methods found in literature utilizing this non local dependency are designed to give competitive results compared to other powerful methods like wavelet based approaches or diffusion techniques. From the survey it is found that non local dependency utilizing not only geometric but also photometric similarity in ultrasound images will help in efficiently removing heavy noise by preserving fine structures that helps in diagnostics.

III. METHOD

A detailed survey on despeckling techniques for ultrasound images is presented in the previous section. For improving despeckling performance exploiting non local dependency is found to be more effective. But compared to classical methods exploiting geometrical redundancy, if photometric redundancy existing in images is also exploited the resulting despeckling performance can be improved. Here a Weiner filter exploiting patch redundancy, exploiting both geometric and photometric similarity is used in denoising ultrasound images. This Weiner filter was designed to give optimal performance in mean squared error (MSE) sense. The algorithm used consist of 2 parts, first is a preprocessing used to convert signal dependent, multiplicative speckle noise into signal independent, additive one and second is the use of patch based Weiner filter to remove this noise.

A. Preprocessing

The multiplicative noise is represented as follows:

$$g(x, y) = f(x, y) \times n(x, y) \tag{2}$$

where f(x,y) is the original image, n(x,y) denotes the noise introduced into the image to produce the corrupted image g(x,y) and (x,y) represents the pixel location. This is converted to additive noise by using log transformation of above equation as follows:

$$\ln(g(x, y)) = \ln(f(x, y)) + \ln(n(x, y)) \tag{3}$$

After this a decorrelation filtering is performed to convert speckle into signal independent noise. This is done by linear filtering.

B. Patch based Weiner filter

This filter first segments the noisy image into patches that are geometrically similar. K-Means clustering using Locally Adaptive Regression Kernels (LARK) features provides a reasonably accurate clustering , even when the input image is contaminated by considerable noise [9]. Then the mean and covariance of these (geometrically similar) noisy image patches are estimated. Next, for each patch in the geometrical cluster, photometrically similar patches are identified where photometrically similar patches are considered to be multiple observations of a single latent patch with difference arising (ideally) due to noise only. For these patches the weights are computed based on their similarity to the reference patch. Then their parameters are used in patch based denoising. To reduce the artefacts occurring in normal patch based methods, here image patches are selected to have some degree of overlap with their neighbours. Finally an aggregation step is used to optimally fuse the multiple estimates obtained for the pixels lying in the patch overlaps to form the denoised image. A patch based locally optimal Weiner filter has been applied for natural images corrupted by additive white Gaussian noise (AWGN) with great success [9]. Here this filter is used in denoising ultrasound images by adding a preprocessing step. The denoised estimate of each patch z_i from its noisy observation y_i can be represented as,

$$\hat{z}_i = \left[\sum_{j=1}^{N_i} \frac{w_{ij} y_j}{\sum_{j=1}^{N_i} w_{ij}}\right] + \sum_{j=1}^{N_i} \frac{w_{ij}}{\sum_{j=1}^{N_i} w_{ij}}$$

$$\left(\sum_{j=1}^{N_i} w_{ij} C_z + I\right)^{-1} (\bar{z} - y_j) \tag{4}$$

Where y_j is the patches photometrically similar to y_i, w_{ij} is the weights assigned to each patch y_j based on their photometric similarity to reference patch, C_z is the covariance matrix and $\bar{z}$ is the mean obtained from the geometrically similar patches within each cluster, and I is the $n \times n$ identity matrix.

IV. RESULTS AND DISCUSSION

A. Evaluation of Proposed Method

Assessment of the restored image quality, is done using quantitative measures as they can dynamically monitor and adjust image quality, optimize parameter settings and can be used to benchmark digital image processing systems. The quantitative measures used in the paper are: Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE). Higher and lower MSE values indicate larger and smaller differences between the original and denoised image respectively. MSE will be equal to zero for identical images. It is calculated as follows:

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{k=1}^{N}\left(X_{j,k} - X'_{j,k}\right)^2 \quad (5)$$

where the image is of size M×N, X and X' are the pixels of original and denoised images. PSNR is the ratio between the maximum possible power of the signal and the noise content. Higher PSNR values show better image quality. For identical images, the MSE become zero and the PSNR is undefined. The representation is given by:

$$PSNR = 10log_{10}\frac{(2^n-1)^n}{MSE} = 10log_{10}\left(\frac{255^2}{MSE}\right) \quad (6)$$

B. Results

The proposed algorithm for denoising an image contaminated by the speckle noise is tested on ultrasound featal image of size 195 × 133. The noisy and denoised image by the method are shown for comparison in figure (2). The effectiveness of the method can be verified by the plot of MSE and PSNR values of different images (featal images of sizes 195 × 133 (image1), 236 × 141 (image2) and 223 × 185 (image3), normal paediatric brain of image size 430 ×352 (image4) and brain with dilated ventricles of image size 430 × 327 (image5)) as shown in figure (3). Further evaluation can be done with the help of table where MSE and PSNR of the proposed method is compared with some of the existing methods as shown in table I. The higher PSNR and lower MSE values shows the effectiveness of the method in despeckling.r The filtered images using different techniques for an ultrasound featal image of size 195×133 is shown in figure (4).

Fig. 2 : Noisy and denoised ultrasound featal image of size 195×133.

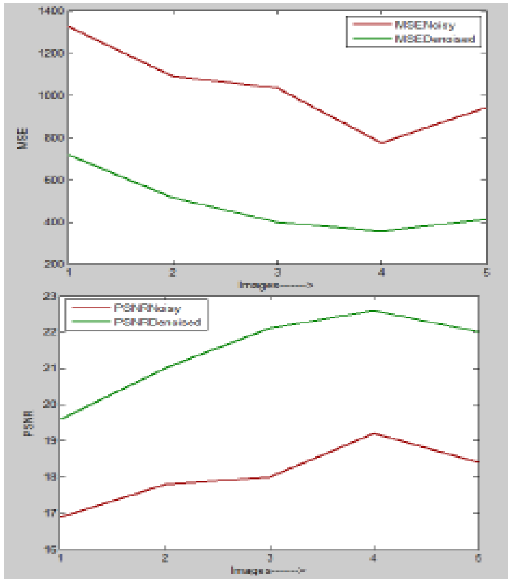

Fig. 3 : Comparison of MSE and PSNR values of 5 different ultrasound images.

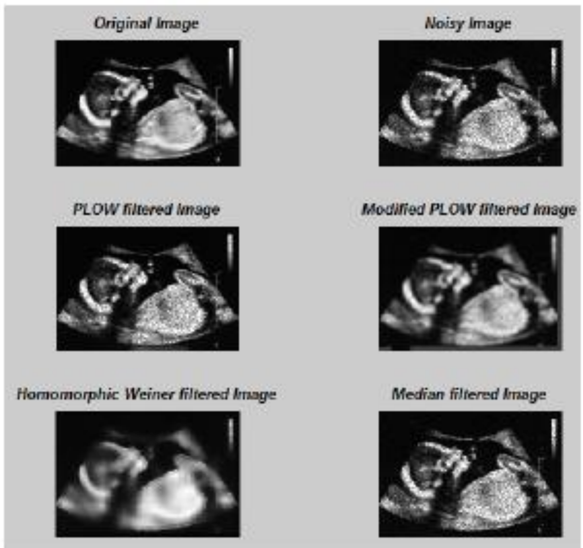

Fig. 4 : Denoised image produced by different filters and proposed filter.

Table I

STATISTICAL DATA ON VARIOUS FILTERS AND PROPOSED FILTER

Filter	MSE	PSNR
Modified PLOW	360.9	22.6
PLOW	562.04	20.6
Weiner	382.37	22.3
Median	637.36	20.1

V. CONCLUSION

Speckle is a major source that cause relatively low Signal to Noise Ratio (SNR) of ultrasound images. Effective despeckling is critical prior to other image processing approaches performed on ultrasound images. Image denoising techniques are very well developed at present time. A detailed survey on these different techniques is presented here.

From the survey it is found that although diverse denoising filters for ultrasound images are available in literature which are termed as edge and feature preserving, they all suffer from limitations. The study also shows that non local models exploiting patch redundancy evolved recently which is found to give best results among other wavelet based approaches or diffusion techniques. Here a Weiner filter exploiting patch redundancy is used in denoising ultrasound images. The resulting denoised images together with PSNR and MSE values shows that the proposed method produces results quite comparable with other existing despeckling methods. A preprocessing step is added here to make the noise in ultrasound image signal independent and thus make it more adaptable to the filter. In future this can be avoided and the method can be modified to be adaptable to speckle noise by itself to further improve the efficiency.

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