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LLRMA and KDE based Ultrasound Image Despeckling

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ABSTRACT

The major issue associated with ultrasound imaging is that it may be corrupted by speckle noise during image acquicition. Speckle pattern is a form of multiplicative noise which blurs the ultrasound images. It reduces the contrast and resolution of ultrasound images which results in poor interpretation of image features. Hence speckle reduction is often used as a preprocessing step for successful use of classical image processing algorithms for image segmentation, classification and pattern recognition. In this work an Ultrasound image despeckling approach based on Local Low Rank Approximation, Kernel Density Estimation and local variance is proposed.

Index Terms: Despeckling, Local Low Rank Approximation, Ultrasound Image Denoising.

I. INTRODUCTION

Ultrasound imaging has been used for decades in medical practice for dicision making and diagnosis. It is comparatively less expensive, safe, accurate and good in forming real time imaging. Ultrasound examinations are painless and easily tolerated by most patients. Image aequisition is based on the principle that when Ultrasound waves travel through tissues they are partly reflected back as echoes to the transducer. The features of the imaging tissue can be interpreted by analysing these echoes. Usually sound waves in the range of 3 to 20 MHz are used in medical ultrasound devices. Selection of transducer frequency plays a vital role in providing optimal image resolution in diagnostic. The major issue associated with ultrasound imaging is that it may be corrupted by speckle noise during image acquicition. Speckle pattern is a form of multiplicative noise which blurs the ultra sound images. It reduces the contrast and resolution of ultrasound images which results in poor interpretation of image features such as textures, edges and point target. Hence speckle reduction is often used as a preprocessing step for successful use of classical image processing algorithms for image segmentation, classification and pattern recognition. Since early 1980s speckle noise reduction has attracted much research attention and has been extensively studied. Many denoising methods have been developed over the years; see [1], [4], [3], [6],[7], [9], [2],[11], [13],[19], [12], [14],[15], [16], [17], [18].

In this work a novel despeckling method which well utilised the Low Rank Approximation and local statistics of the image is proposed. The paper is organized as follows: Section 2 covers the methodology, result is analysed in Section 3 concluding remark and future scope is presented in Section 4; the basic concepts and related work is presented in the following subsection.

1.1. Basic Concepts and Related Work

Low Rank Matrix Approximation (LRMA): Low Rank Approximation is a minimization problem for which the objective is to reduce the rank of the approximating matrix. The rank constraint depends on the complexity of the model that fits the data. Application areas of Low Rank Approximations include image processing,

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signal processing and data analysis. Minimizing Frobenius norm satisfying constraints constructed from the training set is a popular approach of RLMA. The Frobenius norm is a vector norm defined as the square root of the sum of the absolute squares of its elements. The Frobenius norm of an m x n matrix X is defined as (Golub and van Loan 1996[8])

$$\| X \| = \sqrt{\sum_{i=1}^{n} \sum_{j=1}^{m} | X(i,j) |^2}$$

Kernel Density Estimation (KDE) KDE is a fundamental data smoothing problem based on non-parametric way to estimate the probability density function of a random variable. Let $x_1; x_2; :::::\ :\ :\ :\ ; x_n$ be an independent and identically distributed sample of some distribution with an unknown density f. Its kernel density estimator is defined as

$$f_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

where K(:) is the kernel and $h > 0$ is a smoothing parameter. Commonly used kernel functions are uniform, triangular, biweight, triweight, Epanechnikov and normal. The Epanechnikov kernel is optimal in a mean square error sense, [5]

Wiener filter: The Wiener filter is the MSE-optimal stationary linear filter for removing additive noise and blurring. It make use of local image variance and highly smooth the areas with small local variance. For areas with high local variance the smoothing is less. This approach provides better results than linear filtering. It preserves edges and other high frequency information of the images, but time complexity is more than linear filtering.

Lee Filter: It reduces speckle noise while preserving edge details. It was derived from the minimum square error criteria by incorporating statistics methods.

II. METHODOLOGY

In this work an extension of the LRMA called Local LRMA which assumes that the matrix X behaves as a low-rank matrix for some image sub blocks. It is a similar approach used described in [10]. Instead of assuming a global low-rank it assumes that X can be reconstructed from several low-rank approximations of X. Each approximation is accurate in a particular sub block of the matrix. The basic idea is to derive the appropriate low rank for sub blocks based on various statistical measures. To make an initial estimate on the local low rank, sub image blocks of the selected images with known noise are used. For each sub block the approximation is computed as the weighted sum of the low rank approximations of closer sub image blocks. The closeness is evaluated based on the statistical measures such as variance and kernel density estimation.

The procedure is as follows. Estimate the low rank approximation of the selected image set with known added noise. Divide the images into sub image blocks. For each subblock M construct a vector $\vec{M}$ of variance and kernel density estimation. Then find a low rank approximation for the subblock M' which minimize the Frobenius norm:

$$\| \Pi_A (X - M) \|_F$$

Where A is the set of anchor points. The anchor points can be selected in different ways one approach is to select random points and the other approach is to select key points such as corner or edge points. $\Pi_A(M)$ is equal to M(a; b) for (a; b) $\in$ A and 0 otherwise. The image to be denoised is aslo divided into subblocks and an approximation to each image sub block S is obtained as follows:

$$\frac{\sum_{i=1}^{n} \frac{1}{e^{\frac{\|\vec{M}-\vec{S}\|}{\eta}}} * M^{I}}{\sum_{i=1}^{n} \frac{1}{e^{\frac{\|\vec{M}-\vec{S}\|}{\eta}}}} \tag{1}$$

For the performance evaluation of the proposed technique Selected ultra-sound images are rst corrupted by adding speckle noise. Then despeckling is performed by the proposed method.

Algorithm

Input: Noisy data set Output: Denoised dataset

1. Make initial estimate of the low rank approximation using the selected image and noise model
2. Divide the selected set into subimage blocks of size *n* x *n* and for each sub image block M construct a vector $\vec{M}$ of variance and kernel density estimation.
3. Obtain a singular value decomposition for the image subblock. Estimate Low rank approximation for the subblock M' which minimize the Frobenius norm:

$$\| \Pi_{A}(X-M) \|_{F}$$

4. Divide the input noisy data set into sub blocks of size *n* x *n*. For each sub block S construct $\vec{S}$
5. Estimate an approximation for each sub block S based on closer image sub-bloks using Equation 1

Experiments were coducted on original medical ultrasound images in DICOM format and the result is compared with that of Lee filter and Wiener filter , see Figure 4

III. RESULTS AND ANALYSIS

The procedure is implemented in Python and tested with original ultrasound images in DICOM format. Performance of the proposed despeckling method is analyzed for speckle noise of variance ranging from 0:01 to 0:1 in terms of the evaluation measures such as Peak Signal to Noise Ratio(PSNR), Mean Squared Error(MSE), Average, Variance and Structural SIMilarity Index(SSIM) MSE is computed using

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - R(i,j)]^{2}.$$

Where I and R are the original and reconstructed images.

The PSNR is an approximation to the quality of reconstructed image which is computed as:

$$PSNR = 20\log_{10}\left(\frac{MAX_{I}}{\sqrt{MSE}}\right)$$

where MAX^{I} is the maximum possible pixel value of the image.

Structural SIMilartiy Index (SSIM) measures similarity of two images in human eye perception. SSIM metric between two windows x and y of size *n* x *n* is computed as follows:

$$SSIM(x,y) = \frac{(2\mu_{x}\mu_{y} + c_{1})\ (2 * \sigma_{xy} + c_{2})}{\left(\mu_{x}^{2} + \mu_{y}^{2} + c_{1}\right)\left(\sigma_{x}^{2} + \sigma_{y}^{2} + c_{2}\right)}$$

where μ, σ^2 denote the average, variance respectively and c_1; c_2 are the variables used to stabilize the division with weak denominator. $c_1 = (k_1L)^2$; $c_2 = (k_2L)^2$; default values of k_1; k_2 are 0:01 and 0:03 respectively and L is the dynamic range of pixel values. Resultant SSIM value is a decimal in between - 1 and +1. SSIM value 1 is obtained only for two idential sets of data.

$$NCC = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\left(I_{i,j}-\bar{I}\right)\left(R_{i,j}-\bar{R}\right)}{\sqrt{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}(I_{i,j}-\bar{I})^2\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}\left(R_{i,j}-\bar{R}\right)^2}}$$

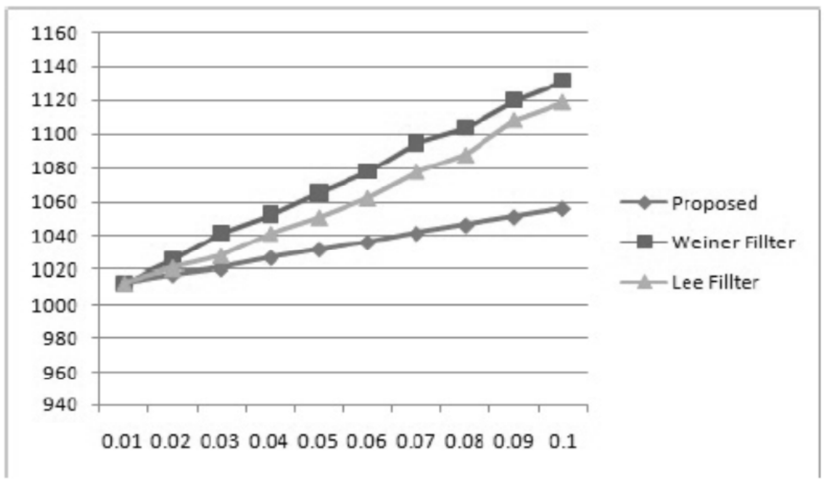

Figure 1: Comparison in terms of Variance

In order to evaluate the performance of the proposed method controlled multiplicative Gaussian noise is added to original Ultrasound images in DICOM format . Performance is evaluated in terms of the evaluation measures PSNR, MSE, Average, Variance and SSIM; the average values are shown in Table 3.

Performance of the proposed method is then compared with that of Weiner Filter and Lee Filter. It is observed that the proposed method outperforms the Weiner and Lee lters for higher noise variance in terms of PSNR, MSE and Variance. The comparative result in terms of PSNR, MSE and Variance are shown in Figures 2, 1 and 3 respectively.

Table 1
Performance Evaluation

Varience	PSNR	MSE	Average	Variance	SSIM	NCC
0.01	36.7133	14.6692	46.6008	1012.6574	0.7231	32.3296
0.02	35.5103	20.3569	46.6109	1017.6075	0.6863	32.331
0.03	34.5547	26.4175	46.6069	1021.0741	0.6538	32.3167
0.04	33.7737	32.5699	46.6074	1026.6725	0.6265	32.3144
0.05	33.1095	38.8492	46.6114	1031.6465	0.6024	32.311
0.06	32.5311	45.2897	46.609	1036.1987	0.5806	32.2997
0.07	32.0192	51.8128	46.6102	1041.5266	0.5616	32.2948
0.08	31.568	58.1586	46.6075	1046.4329	0.5448	32.2869
0.09	31.155	64.6871	46.606	1051.1983	0.5291	32.2773
0.1	30.7782	71.1867	46.6019	1056.1688	0.5145	32.2682

IV. CONCLUSION

In this work a despeckling technique using Local Low Rank Approximation is proposed and tested for original ultrasound images. The novelty of this approach is that instead of having a global low rank approximation, a weighted average of the low rank approximations based on local image statistics is used. This approach helps in more accurate estimation of pixel intensities. Experiments show that local low-rank approximation is significantly more accurate than global low-rank approximation. The proposed method outperforms the despeckling filters such as Weiner and Lee filter in terms of PSNR, MSE and Variance values.

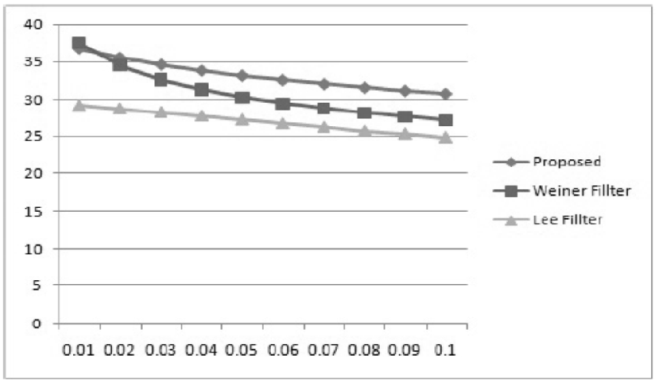

Figure 2: Comparison in terms of PSNR

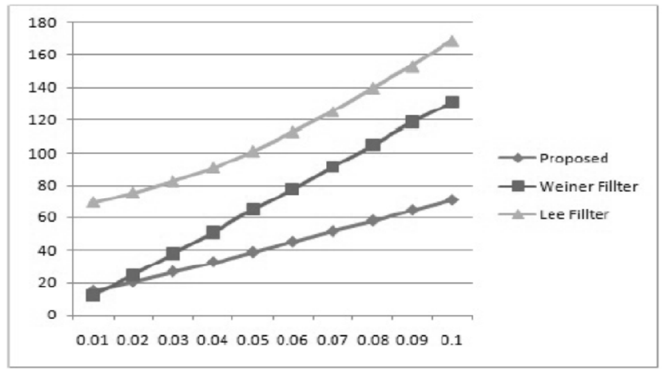

Figure 3: Comparison in terms of MSE

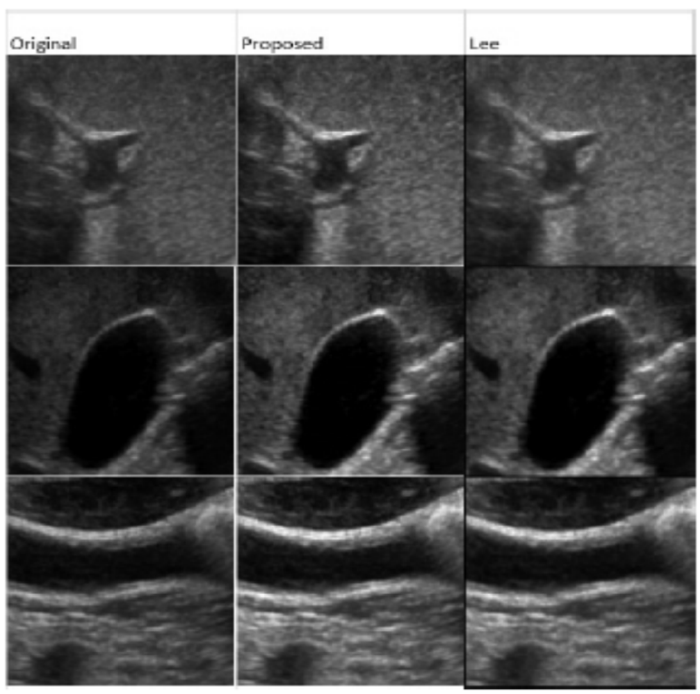

Figure 4: Original Image, denoised images using Proposed and Lee filters

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