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Quantum-Inspired Weighted Bilateral Filtering for Despeckling in Ultrasound Images

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***Abstract* — The ultrasound is a nondestructive technique used widely in the medical field for detection of soft tissues in the human body. But this should be validated by an expert radiologist, since ultrasound images are highly affected by noises. In this paper four methods for denoising the speckle noise are compared and analyzed, namely, diffusion tensors, heavy-tailed Levy's distribution, quantum inspired bi-lateral filtering and locally adaptive wavelet domain Bayesian processor. Performances of each method were quantified by means of Peak Signal to Noise Ratio (PSNR) and Mean Structural Similarity Index Matrix (MSSIM). It was found that denoising of US images through QWBF has higher PSNR value of 16.75 and MSSIM of 0.88. Hence this method was proved to be more efficient compared to other three methods presented in this paper.**

Keywords—Diffusion tensors; Heavy-tailed Levy's distribution; Quantum inspired bi-lateral filtering; Locally adaptive wavelet domain Bayesian processor.

I. INTRODUCTION

Ultrasound imaging techniques under application for roughly over a century. Austrian neurologist, Dr. Karl Theo Dussik, was the earliest to apply ultrasound as a medical analytic tool for brain imaging [14]. Ultrasound Imaging is portable, non-invasive, radiation risk and cost effective at a lesser price. Also US imaging provides cross-sectional view of the tissues and organs making it "tomographic" [14]. In spite of many benefits of Ultrasonography, quality of the image is highly sensitive to noise called "speckle". In the medical prose, speckle is dealt with as an exasperating antique as it figures out how to exacerbate the determination and the item perceptibility. Furthermore, in US pictures, on every axis the speckle noise has a spatial connection length, same as the determination of the span of the cell [9]. This makes it very difficult to remove the noise while preserving the features. Hence a trade-off has to be made in any technique. Speckle follow a granulated pattern because of the underlying coherent waves in image formation.

Speckle reduction techniques can be categorized as averaging approaches, resolution enhancement approaches and post-processing approaches [3]. Speckle noise is an outcome of closely located reflectors within a resolution cell. Therefore enhancing the resolution could potentially eliminate speckle noise [3]. Averaging approaches average multiple decorrelated frames and it includes spatial compounding, frequency compounding and temporal averaging. However, averaging techniques provide limited speckle reduction and reduce frame rate, making the technique for limited practical usage [3]. Commonly, post processing approaches have been adopted for speckle reduction which includes median filter, Weiner filter and diffusion filters. Adaptive filters such as Weiner filter, Lee filter, Kuan filter and Frost filter employ sliding window to estimate all pixels' statistical information using the local mean and local variance [3]. Strong blurring effects occurs when the filter size is higher than 3×3 and hence has deprivation in resolution [3].

In the most recent couple of years, the utilization of non linear PDEs strategies including anisotropic dissemination has detectably developed and is a critical apparatus in current picture handling. The idea after the anisotropic dissemination is to incorporate an adaptative smoothness imperative in the denoising movement. That is, the smooth is bolstered in a homogeneous district and discouraged around limits, so as to protect the discontinuities of the picture. Total Variation (TV) model and the anisotropic smoothing model are the best devices for picture denoising [4].

This paper is organized as follows. Section 2, discusses the various techniques that have been implemented for the speckle denoising. Section 3, focuses on experimental results and comparison. Section 4, gives the conclusion.

II. DENOISING TECHNIQUES

A. Diffusion Tensors

The structure tensor gives a more upgraded picture of nearby examples pictures. This is superior to a simple gradient. Taking into account its eigenvalues and the comparing eigenvectors, the tensor aggregates up the principle directions of the gradient in a predetermined neighborhood of a point, and the extent to which those directions are cognizant [4].

It is vital utilizing the strategies which think about the orientation of the gradient and the flow towards the orientation of intriguing components with a specific end goal to distinguish properties, for example, corners or to decide the neighborhood rationality of structures. This can be basically accomplished by utilizing the structure tensor, likewise alluded to the second minute grid. For a multivalued picture, the structure tensor has the subsequent structure [4]:

$$s_\sigma = (\sum_{i=1}^{n} \nabla u_{i\sigma} \nabla u_{i\sigma}^T) = \begin{bmatrix} \sum_{i=1}^{n} u_{ix\sigma}^2 & \sum_{i=1}^{n} u_{ix\sigma}\, u_{iy\sigma} \\ \sum_{i=1}^{n} u_{ix\sigma}\, u_{iy\sigma} & \sum_{i=1}^{n} u_{iy\sigma}^2 \end{bmatrix}$$
(1)

Let $u(x, y, t): \Omega \to R$ be the gray-scaled intensity image with a diffusion time t, for the image domain $\Omega \in R^2$.

With $\nabla u_{i\sigma} = K_\sigma * \nabla u_i = K_\sigma * (u_{ix}, u_{iy})$: the smoothed form of the inclination which is acquired by a convolution with a Gaussian kernel K_σ. The structure scale σ decides the extent of the subsequent stream like examples [4].

Then again, it is more appropriate to utilize a smoothed variant of s_σ [4],

$$J_\rho = K_\rho * S_\sigma = \begin{bmatrix} j_{11} & j_{12} \\ j_{21} & j_{22} \end{bmatrix} \qquad (2).$$

Where K_ρ: a Gaussian portion with standard deviation ρ. The integration scale ρ midpoints orientation data. In this way, directional conduct of the channel will be steady.

The non-linear PDE structure is given by [4],

$$\partial_t u = div(g(|\nabla u|)\nabla u) \ on\ \Omega(0, \infty) \qquad (3).$$

Where $\partial_t u$ signifies the principal subsidiary of the dispersion time t; |∇u|: indicates the slope modulus and g(.) is a diminishing capacity, known as the diffusivity capacity which permit isotropic dissemination in level districts and no dissemination close edges.

The concept of non-linear diffusion tensor is obtained by supplanting the diffusivity capacity g(.) in (3) with a structure tensor J_ρ, to make a genuinely anisotropic plan [4],

$$\partial_t u = div(D(J_\rho)\nabla u) \qquad (4).$$

Where D(.) is the diffusion tensor which is sure positive symmetric 2x2 lattice.

B. Heavy-tailed Levy's distribution

The speckle noise in ultrasound imaging is modelled as a multiplicative process, because fully developed speckle has constant signal-to-noise ratio [1]. Let speckle noise be modelled using gamma distribution,

$$p_n(n) = \frac{\beta^\alpha}{\Gamma(\alpha)} n^{\alpha-1} e^{-n\beta} \qquad (5).$$

Where $\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt$ with mean α/β and variance α/β^2.

Let the log-transformed observed signal y is given by

$$y = x + s \qquad (6).$$

Where x and s denote the log-transformed noise free image which has to be recovered and the noise, respectively. The observed signal y is decomposed using J-level DTCWT and it yields one approximation subband and six directional subbands oriented at ±15°, ±45° and ±75°.

$$g_j^i = w_j^i + n_j^i \qquad (7).$$

These are the DTCWT coefficients for y, x and s, respectively. The DTCWT coefficient w_j is modelled using heavy-tailed Levy's distribution and is given as,

$$p_{w_j}(w_j) = \sqrt{\frac{c_j}{2\pi}} \frac{\exp\left(-\frac{c_j}{2(w_j-\mu)}\right)}{\sqrt[3]{(w_j-\mu)}} \ for\ 1 \le j \le J \qquad (8).$$

Where μ is the shift parameter and c is the scale parameter.

C. Quantum inspired bi-lateral filtering

The bilateral filter is an efficient local denoising method, which can smoothen images while keeping edges. It combines domain and range filtering and exploits the closeness and similarity of image pixels, which refer to the vicinity in the domain and range, respectively [5].

$$\hat{I}(x) = \frac{\int_{x_o \in N} f_s(x, x_o) f_r(I(x), I(x_o)) I(x_o) dx_o}{\int_{x_o \in N} f_s(x, x_o) f_r(I(x), I(x_o)) dx_o} \qquad (8).$$

Where I and ˆI denote the speckled image and the resulting image, respectively. x is the filtered pixel. N represents the window space of the neighborhood region. $f_r(.)$ is the similarity function,

$$f_r(I(x), I(x_o)) = \exp\left(-\frac{\|(I(x) - I(x_o))\|^2}{2\sigma_r^2}\right) \qquad (9).$$

Where $\|(I(x) - I(x_0))\|^2$ is the absolute difference of the pixel value difference. σ_r is the standard deviation and determines the filtering performance.

$f_s(\cdot)$ is the closeness function,

$$f_s((x), (x_o)) = \exp\left(-\frac{\|((x) - (x_o))\|^2}{2\sigma_s^2}\right) \qquad (10).$$

Where $\|x - x_0\|^2$ is the Euclidean distance between x and x_0. The standard deviation σ_s should vary with the contamination level of the speckle noise. Then an overall filtered image Y is obtained by the proposed Quantum-inspired Weighted Bi-lateral Filter (QWBF) [5],

$$\hat{Y} = (1 - w)\hat{I}_{\sigma_s min} + w\hat{I}_{\sigma_s max} \qquad (11).$$

Where w is a proposed quantum-inspired weight. By adapting the basic the principle of Quantum Signal Processing (QSP), the weight is a superposition state of the noise and the signal,

$$w\rangle = a.0\rangle + b.1\rangle \qquad (12).$$

Where noise |0⟩ and signal |1⟩ are ground states in the QSP framework. a and b are probability amplitudes of the ground states |0⟩ and |1⟩, respectively.

D. Locally adaptive wavelet domain Bayesian processor

A measurable way to deal with speckle noise reduction in US pictures taking into account most extreme a posteriori (MAP) estimation in the wavelet area. The technique proposes a locally adaptive Bayesian processor by consolidating the MAP estimation accepting speckle noise is spatially corresponded inside a little window and

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parameters are ascertained from the neighboring coefficients. Also, the neighborhood estimator is stretched out to the repetitive wavelet representation, which gives preferred results over the pulverized wavelet change [9].

Pdf for a Rayleigh distributed random variable, x, is defined as [9],

$$p(x) = \frac{x}{\alpha^2} exp\left(-\frac{x^2}{2\alpha^2}\right), \quad x \geq 0 \qquad (13).$$

Where x is the amplitude of the noise and α is the fading parameter. The pdf of a zero-mean Gaussian distributed random variable, n, is defined as follows [9],

$$p_n(n) = \frac{1}{\sigma_n\sqrt{2\pi}} exp\left(-\frac{n^2}{2\sigma_n^2}\right) \quad -\infty < n < \infty \qquad (14).$$

Where σ_n the standard deviation of signal, is n, determines the spread of the density function.

The wavelet transformation is a straight operation, in this manner the utilization of redundant orthogonal discrete wavelet transform (RDWT) to the noise image, d, gives [9],

$$y_{l,k}^j = x_{l,k}^j + \varepsilon_{l,k}^j \qquad (15).$$

Where y, x and ε are the irregular variables speaking to uproarious wavelet coefficients, genuine coefficients and commotion, separately, in different point of interest sub groups (HL_j; LH_j; HH_j), j fluctuating from 1, 2 . . . J, and J is the aggregate number of disintegrations. The wavelet area Bayesian techniques are utilized to prepare every coefficient $y_{l,k}$ from the point of interest subbands nonlinearly to acquire $\hat{x}_{l,k}$ [9],

$$\hat{x}(y) = sign(y) \times max\left(0, \frac{\left(2|y|\sigma_x^2 + \alpha^2|y| - \sqrt{\alpha^4 y^2 + 4\alpha^4\sigma_x^2 + 4\alpha^2\sigma_x^4}\right)}{2(\alpha^2 + \sigma_x^2)}\right) \qquad (16).$$

Where $\hat{x}(y)$ is a component of blurring parameter α and signal fluctuation σ_x^2, the estimator has been made spatially versatile, i.e. the parameter σ_x is registered for every wavelet coefficient independently from the nearby neighborhood utilizing an altered size sliding window [9].

III. EXPERIMENTAL RESULTS

In this segment, the execution of the above looked at denoising calculations is examined as far as Peak Signal To Noise Ratio (PSNR) and Mean Structural Similarity Index Matrix (MSSIM).

PSNR is defined as [1],

$$PSNR = 10 \log \frac{255^2}{MSE} \qquad (17).$$

Where MSE is the mean square error between the original and the denoised image.

MSSIM is defined as [1],

$$MSSIM(x, y) = \frac{1}{M}\sum_{i=1}^{M} SSIM(x_i, y_i) \qquad (18).$$

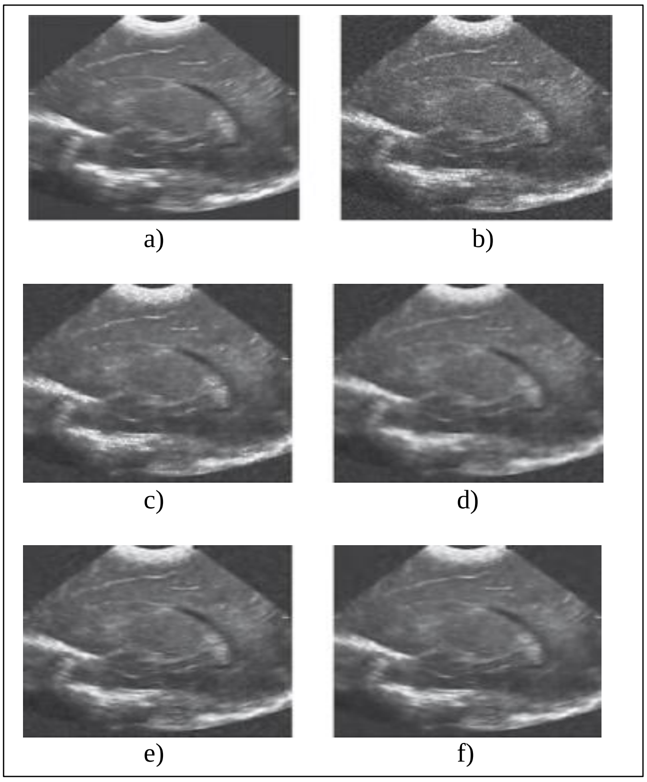
Where X, Y are the first and denoised picture, individually. M is the quantity of neighborhood windows in the picture and SSIM is given by [1],

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2\mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (19).$$

Where σ_x, μ_x and σ_y, μ_y denote the mean intensities and standard deviation of the image contents of X and Y, respectively, at the jth local window. σ_{xy} can be estimated as [1],

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y) \qquad (20).$$

Fig. 1 Medical Ultrasound Image Despeckling Experiment.



a) Original image.
b) Speckled image with standard deviation 0.9.
c) Diffusion Tensor method.
d) Heavy-tailed Levy's distribution method.
e) Locally adaptive wavelet domain Bayesian processor method.
f) Quantum inspired weighted bi-lateral filter method.

The first pixel intensities before being defiled by speckle noise are to be known ahead of time keeping in mind the end goal to compute PSNR and MSSIM. A spotted picture is created by duplicating a clamor free picture with the dot commotion with fluctuation $\sigma^2 = 0.81$. The spot commotion is reproduced utilizing the Gamma distribution. MATLAB® toolbox developed by Kingsbury et al. is used for DTCWT implementation [1].

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Table. 1 Performance analysis of Fig. 1.

	Speckled	Diffusion Tensor	Heavy-tailed Levy's	Locally adaptive wavelet Bayesian	QWBF
PSNR	9.64	13.83	15.10	16.12	16.75
MSSIM	0.60	0.77	0.82	0.85	0.88

IV. CONCLUSION

Thus four effective methods have been compared for despeckling in medical ultrasound images. It can be visualized that denoising performed using QWBF has higher PSNR and MSSIM values. It was found to have PSNR of 16.75 and MSSIM of 0.88. Hence out of the four methods compared, QWBF stands out to have a better Despeckling capability because of its adaptive and edge preserving features. Furthermore, it provides better approaches to take care of medical image processing issues. Trial results utilizing genuine therapeutic pictures show that this technique have focused exhibitions in bracing down speckle noise and protecting points of interest for medicinal ultrasound pictures. These results indicate that the presented method could assist the radiologists in the diagnosis of medical diseases using Ultrasound Imaging technique.

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