Denoising Based on Spatial Filtering in Ultrasound Images

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Abstract— **In Ultrasound images, speckle noise is inherent in medical ultrasound images and it is the cause for decreased resolution and contrast-to-noise ratio. The presence of speckle noise is not attractive as it reduces the image quality and it affects the tasks of individual interpretation and diagnosis.**

Image variance is a granular noise that exists inherently in Ultrasound image which degrades image quality. Speckle noise reduction is one of the most important processes to enhance the quality of Ultrasound images. Before using the images of the Ultrasound for diagnosis, the first step is to reduce the effect of speckle noise. Most speckle reduction techniques have been studied by researchers; but there is no comprehensive method that takes into account all the constraints. Filtering is one of the standard methods used to reduce speckle noise. This paper is the study of different spatial filtering for speckle noise reduction and taking more emphasis on denoising based on wavelet transform.

Keywords— Speckle noise, Spatial domain filter, Wavelet based threshold techniques, visu shrinkage, sure shrinkage

I. INTRODUCTION

Unlike many other imaging applications where image quality de-noised estimates for how nice visual interceptions giving the human eye, medical applications require some restrictions, such as generating device that could be misinterpreted as clinically interesting features to achieve the best possible diagnosis, it is important that ultrasound medical images are crisp, clear, and removing noise and artifacts. While technologies the acquisition of digital medical images to improve Ultrasound persist, resulting in images of higher resolution and higher quality, noise remains a problem for many medical images. The elimination of noise in these images of each residue of the main challenges in the study of different filters.

In this paper, the importance of such situations and develops highlights some of the requirements that must be met to be of better help in the actual clinical analysis. In General, there are two techniques eliminate / reduce speckle noise, i. e, the process of multi-appearance and spatial filtering. Multiple look process is used in the data acquisition stage, while the spatial filtering is used after the data is stored. No matter what method is used to reduce / eliminate speckle noise, must preserve radiometric information, edge information and last but not least, the spatial resolution. These are the conditions that any technique of speckle noise reduction to meet. In this case, Spatial filtering techniques used for reducing speckle ultrasound images.

II. SPECKLE NOISE

Spotted is not an image noise, but noise-like Contrast variation. It arises from arbitrary variations in the strength of waves backscattered objects and is observed mainly in medical imaging. Reduction spots medical ultrasound imaging is a critical pre-processing step, providing clinicians with enhanced diagnostic capability.

- Noise is the characteristic mottling seen in topographic images contributing calculated the visual noise.

- Some filtering techniques applied to speckle noised image

A. Speckle Filtering

Speckle filtering involves moving a kernel on each pixel of the image and application of a mathematical calculation using the pixel values under the core and replacing the central pixel with the calculated value. Stir the core along the image of a pixel at a time until the entire image has been covered. By applying the smoothing filter result is achieved and the visual appearance of speckle is reduced.

1. Median filter

Median filter is defined as the median of all pixels within a local region of an image. It performs much better than the arithmetic mean filter to remove salt and pepper noise in an image and preservation of spatial data contained in the image. This method is especially effective when the noise pattern consists of a strong peak as the components and the function is to preserve sharp edges. The main disadvantage of the median filter is the extra computation time needed to sort the intensity value of each set.

2. Lee & Kaun Filters

Lee filter [1] form an output image by calculating a linear combination of the intensity of the center pixel in a filter window with the average intensity of the window. Lee and Kaun filter are similar formulation, although the signal model assumptions and derivations are different. These two filters to achieve a balance between the straight forward averaging in homogeneous regions and filter identity in which there are edges and point features. This equilibrium depends on the coefficient of variation within the moving window. The main drawback of Lee filter is that it tends to ignore speckle noise near edges. It also incompetent of removing high frequency noise and it cannot remove noise in high and low variance regions.

An improved version of lee filter known as enhanced lee filter (Enh Lee) which eliminates the demerits of lee filter mentioned above.

3. Frost Filter [2]

Averaging balance and all pass filter by forming a filter core is achieved exponentially. The filter response varies in the neighbourhood with the coefficient of variation.

4. Weiner Filter

Using deconvolution function to despeckle an image using Wiener filter [3]. Wiener deconvolution can be used efficiently when the frequency characteristics of the image and the additive noise, at least to some degree are known. Wiener filter performs smoothing of the image based on the computation of local image variance. When the local variance of the image is large the smoothing is little on the other hand if the variance is small, smoothing will be better.

5. Diffusion Filter

Diffusion filters [4] remove noise from an image by modifying the image through the solution of a partial differential equation (PDE). Smoothing is performed according to the edges of the image and their directions. Anisotropic diffusion is an efficient nonlinear technique to perform while improving contrast and noise reduction. Softens homogeneous image areas but preserves image edges without information of the power spectrum of the image, can, therefore, be directly applied to images.

a) SRAD Filter

SRAD filter [5] is known as speckle reduction anisotropic diffusion. The SRAD can remove speckle without distorting useful image information and without destroying the edges of important images. PDE SRAD exploits the instantaneous coefficient variation in speckle reduction. SRAD algorithm provides superior performance[6] compared to conventional techniques such as Frost, Kaun filters in terms of smoothing and preserving edges and features.

Diffusion methods mentioned above can maintain or even improve the prominent edges to remove speckle. However, the methods have a common limitation in retaining subtle features such as small cysts and lesions in ultrasound images.

A modified SRAD filter based on Kaun filter properly Lee filter was developed and this approach is called Detail preserving anisotropic diffusion (DPAD) .This method is combined with the method of anisotropic diffusion matrix designed to preserve and enhance the small structures of the vessels referred to as speckle reduction oriented anisotropic diffusion.

6. Denoising Based Threshold Wavelet Transform

The basic theory for the wavelet thresholding wavelet coefficients is assumed that there is a number of wavelet coefficients that are contaminated very small or near zero serious. Thus, a threshold can be used to remove contaminated to remove noise spots.

Another reason for using wavelet transformation due to the development of efficient algorithms for the decomposition of and reconstruction [7] signal to the image processing applications, such as noise removal and compression. In [8], the authors have presented a method of suppressing mottled novel images of medical ultrasound, in which it is shown that the decompositions sub band ultrasound images have significantly not Gaussian statistics that are best described by families of distributions heavy tail, such as alpha stable. Then, a Bayesian estimator is designed to exploit these statistics. Alpha stable model is used to develop a processor to eliminate blind noise a nonlinear operation on the data. In [9], the authors have proposed a new technique for despeckling of medical ultrasound images using lossy compression. In [10], the authors have proposed a new wavelet technique denoising image based, in which the different functions of threshold, that is, the universal threshold Visu shrinkage safe shrink, Bayes shrinkage and normal shrinkage are considered to the study. The threshold value kernel using circular half maximum threshold, the nearest neighbor and new threshold function is calculated.

Any decomposition of an image into wavelets involves a pair of waveforms, one to represent the high frequencies corresponding to the detailed portions of an image (wavelet function ψ) and one for high frequencies with short transform functions (low level). The result of WT is a set of wavelet low or smooth parts of an image (scalar function φ) coefficients measuring the contribution of small waves at different locations and scales frequencies. The WT performs multiple image analysis [11] resolution.

a) *Thresholding techniques*

There are two approaches for thresholding after calculating the wavelet coefficients, namely the sub band thresholding and global threshold [12]. In sub band thresholding, the noise variance of horizontal, vertical and diagonal of each sub-band decomposition level is calculated from the outer spectral bands and move towards the inner spectral bands (decay from higher levels to the levels lower) and calculated the threshold value using Bayes shrinkage or visu shrinkage . Global thresholding, we determine the threshold value of the diagonal band but only apply this threshold for horizontal, vertical and diagonal sub bands. This approach assumes that the diagonal band contains most of the high frequency components; therefore the noise content in the diagonal band should be higher than the other bands. Thicker threshold level is not, because it contains the approximation coefficients representing the translated and reduced version of the original image. Threshold at this level makes the image distorted reconstruction.

b) Shrinking Scheme

The threshold approach is to reduce the detail coefficients (high frequency components) whose amplitudes are smaller than a certain threshold value statistical zero while retaining the softer detail coefficients to reconstruct the ideal image without much loss in its details. This process is sometimes known as the wavelet shrinkage, as the detail coefficients shrunk towards zero. Three schemes to reduce the size of the wavelet coefficients, namely the keep-or-kill hard thresholding, soft thresholding shrinkage or kill introduced by [13] and the recent semi soft or firm threshold. The wavelet coefficient is reduced more efficiently if the coefficients are limited, that is, most of the coefficients are zero and a minority of coefficients with magnitude greater than can render the image [14]. The criteria for each scheme is described as follows. Since λ denotes the threshold limit, X_w denotes the input wavelet coefficients and wavelet coefficients denote Y_t-out threshold, we define the following threshold function:

Hard threshold:

$$T_{hard}\ Y_t = (X_w) \qquad (1)$$
$$= X_w,\ \text{for}\ |X_w| \geq \lambda$$
$$0,\ \text{for}\ |X_w| < \lambda$$

Soft thresholding:

$$T_{soft}\ Y_t = (X_w) \qquad (2)$$
$$\text{Sign} = X_w\ (|X_w| - \lambda)\ \text{for}\ |X_w| \geq \lambda$$
$$0,\ \text{for}\ |X_w| < \lambda$$

Semi soft thresholding:

$$T_{semisoft}\ Y_t = (X_w) \qquad (3)$$
$$= \{0,\ \text{for}\ |X_w| \leq \lambda\ \text{sign}\ \{X_w\}$$
$$\lambda_1\ (|X_w| - \lambda)$$
$$\lambda_1 - \lambda\ \text{for}\ \lambda < |X_w| \leq \lambda_1$$
$$X_w,\ \text{for}\ |X_w| > \lambda 1$$

where $\lambda_1 = 2\lambda$.

Hard procedure removes noise threshold only by thresholding wavelet coefficients of detail subbands , keeping unchanged the low resolution coefficients. Soft threshold scheme shown in Eq. (2) is an extension of hard thresholding. Discontinuities are avoided and are therefore more stable than the hard threshold. In practice, soft thresholding is more popular than hard thresholding, since it reduces the sudden abrupt changes that occur in hard thresholding and provides more visually pleasing images recovered.The goal of semi-soft threshold to offer a compromise between the hard and soft thresholding changing the gradient of the slope. This scheme requires two thresholds a λ lower threshold and upper threshold λ_1 where λ_1 is estimated to be twice the lower threshold value λ.

c) Shrinkage Rule

A large λ threshold is reduced almost all coefficients to zero and may result in more than soften the image, while a small value of λ will lead to sharp edges with the details that are preserved, but may fail to suppress speckle. We use the rules of shrinkage, that is, the Visu shrinkage and Bayes threshold for contraction are explained in the following:

i. Universal Threshold

The universal threshold can be defined as,

$$T = \sigma\sqrt{2logN} \qquad (4)$$

N being the length of the signal, σ is the noise variance is well known in the literature as the universal wavelet threshold. It is the optimal threshold asymptotic direction and minimizes the cost function of the difference between the function. Presumably the universal threshold can give a better estimate of the soft threshold if the number of samples is large [15] [16].

ii. Visu Shrink

Visu Shrink was introduced by Donoho [15]. It uses a threshold value t is proportional to the noise standard deviation. It follows the rule of hard threshold. An estimate of the noise level σ was defined in terms of the mean absolute deviation given by

$$\sigma^2 = \left[\frac{median(|x_{ij}|)}{0.675}\right] \qquad x_{ij} € HH1 \qquad (5)$$

$$t_v = \sigma\sqrt{2\log n} \qquad (6)$$

Which X_{ij} corresponds to the detail coefficients in the wavelet transform. Visu Shrink does not address minimize the mean square error. Another disadvantage is that it cannot remove speckle. It can only deal with additive noise. Visu Shrink follows the scheme overall threshold, which is generally to all wavelet coefficients [17].

iii. SURE Shrink

A threshold chooser based on Stein's Unbiased Risk Estimator (SURE) was proposed by Donoho and Johnston and is called as Sure Shrink. It is a combination of universal threshold and the SURE threshold [18] [19]. This method specifies a threshold value tj for each resolution level j in the wavelet transform is called threshold level dependent. The aim of Sure Shrink is to minimize the mean square error [9] defined as,

$$MSE = \frac{1}{n^2}\sum_{x,y-1}^{n}(Z(x,y) - S(x,y))^2 \qquad (7)$$

Where Z (x, y) is the estimate of the signal S (x, y) is the original signal without noise and n is the size of the signal. Sure Shrink removes noise threshold empirical wavelet coefficients. The course Shrink threshold t * is defined as

$$t^* = \min(t, \sigma\sqrt{(2log\ n)} \qquad (8)$$

Where represents the value unbiased estimator that minimizes the risk of Stein, the noise variance is calculated from the equation, and the image size. It is adaptive smooth, which means that if the unknown function comprises abrupt changes or boundary of the image, the reconstructed image is also does.

iv. Bayes Shrink

Bayes Shrink was proposed by Chang, Yu and Vetterli. The purpose of this method is to minimize the Bayesian risk, and hence its name, Bayes Shrink [19]. Bayes , t_B , the threshold is defined as

$$t_B = \frac{\sigma^2}{\sigma_s} \tag{9}$$

Where σ^2 is the noise variance and σ_s is the variance of the noise-free signal. The noise σ^2variance is estimated from the sub-band HH the median estimator shown in Eq. (9). We have the definition of additive noise

$$w(x,y) = s(x,y) + n(x,y) \tag{10}$$

Since the noise and signal are independent of each other, we can say that

$$\sigma_w^2 = \sigma_s^2 + \sigma^2 \tag{11}$$

σ_w^2 Can be calculated as shown below:

$$\sigma_w^2 = \frac{1}{n^2} \sum_{x,y-1}^{n} w^2(x,y) \tag{12}$$

The signal variance, $\sigma_s^2$is calculated as

$$\sigma_s = \sqrt{\max(\sigma_w^2 - \sigma^2, 0)} \tag{13}$$

with and, Bayes threshold is calculated from Eq.(12). Coefficients Using this threshold, the wavelet are on the threshold of each group .

III. CONCLUSION

The study of various speckle reducing filters for ultrasound images shows that wavelet filters outperforms the other standard speckle filters. Although all standard speckle filters perform well on ultrasound images but they have some constraints. These filters operate by smoothing over a fixed window and it produces artifacts around the object and sometimes causes over smoothing. Wavelet transform is best suited for performance because of its properties like sparsity, multiresolution and multiscale nature. Thresholding techniques used with wavelet are simplest to implement and more to explore.

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