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Speckle Reduction of Ultrasound Image Based on Contourlet Transform

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Abstract- This paper presents a contourlet based approach for speckle reduction of ultrasound image. The discrete wavelet transform provides a transformation of a signal from the time domain to the scale-frequency domain. However, they do not handle high order singularities as well. Curvelets and ridgelets take the form of basis elements which exhibit very high directional sensitivity and high anisotropic. But, it is time consumption to digitize the curvelet transform. This will conduce to a serve limitation on curvelets in certain applications, such as ultrasound imaging and compression.

The contourlet transform have a double iterated filter bank structure and a small redundancy at most 4/3. Based on contourlet transform, two thresholding methods are used. The experiment shows great promise for speckle reduction of breast ultrasound images.

Keywords: contourlet, speckle, ultrasound image.

1. Introduction

There are many methods be used for early detection of disease diagnosis. But, ultrasound is relatively inexpensive, non-invasive, and can be performed in a regular clinical office outside of hospital settings. However, ultrasound image are often difficult to interpret because of the presence of speckle noise. Speckle is multiplicative noise and is mainly reason to make ultrasound image degenerate. We adopt Jain’s [1] speckle noise model to carry out our scheme. There has been active research on denoising with the wavelet transformation. Donoho [2] had suggested that thresholding of wavelet coefficients would denoise signals. However, in 2-D the wavelet transform do not handle higher order singularities as well. Because the 2-D wavelet transform is a separable transform, a tensor product of two 1-D wavelet transforms. Thus, we can not expect that will have any directional sensitivity in 2-D wavelet domain. Recently, curvelet [3] has been proposed, that offers a sparse expansion for 2-D piecewise smooth functions in $\Re^2$ where the discontinuity curves are smooth. But curvelets are based on multiscale ridgelets combined with a spatial bandpass filtering operation in order to isolate different scales. Hence, it is time consumption to digitize the curvelet transform. This will conduce to a serve limitation on curvelets in certain applications, such as ultrasound imaging and compression.

Minh and Vetterli [4] proposed contourlet transform that have a double iterated filter bank structure and a small redundancy at most 4/3. In this paper, we based on contourlet transform and two thresholding methods are used in speckle reduction. The experiment shows great promise for speckle reduction of breast ultrasound images.

The outline of the paper is as follows. Section 2 introduces the contourlet transform. Section 3 describes the speckle reduction algorithm. Finally, Section 4, 5 represented experimental results and conclusion respectively.

2. Contourlet Transform

The discontinuities of natural images where are generated by edges-referred to points in the image with sharp contrast in the intensity, whereas edges are often gathered along smooth contours that are created by typically smooth boundaries of physical objects.

The efficient representation of signal is the critical part of many image processing tasks, including denoising, compression, feature extraction, and enhancement problems. Efficient representation of signal means that we can use sparse description to capture the significant information about an object of interest. Several approaches in developing efficient representations of geometrical regularity been proposed. Candes and Donoho [5] proposed curvelet that offers a sparse expansion for 2-D piecewise smooth functions in $\Re^2$ where the discontinuity curves are smooth. The curvelet transform was developed in the continuous domain via multiscale filtering and then applying a block ridgelet transform [6] on each bandpass image. Candes and Donoho [7] proposed refinement edition of curvelet transform that was defined via frequency partitioning without using the ridgelet transform. However, curvelet construction require a rotation operation, it is a challenging for implementation for discrete images. Minh and Vetterli [6] proposed contourlet transform in 2002. The different between the contourlet and others methods of multiscale and directional image representation is contourlet transform offers different number of directions at each scale while achieving nearly critical sampling.

2.1 Contourlet Scheme

Minh and Vetterli [6] proposed the approach of Contourlet transform called pyramidal directional filter bank (PDFB). In PDFB, the Laplacian pyramid [7] is first used to capture the point discontinuities, then followed by a directional filter bank (DFB) [8] to link point discontinuities into linear structures as shown in Figure 1.

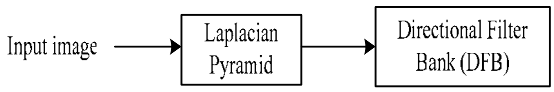
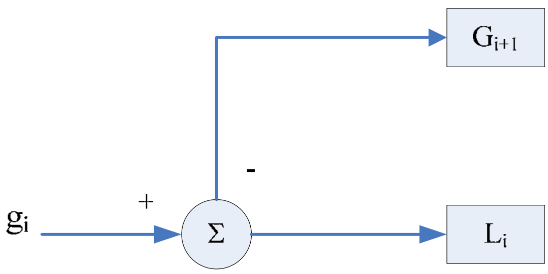


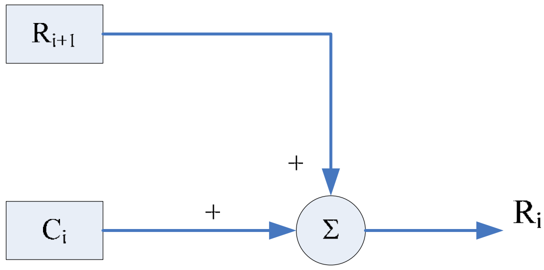
Fig. 1. The diagram of contourlet transforms.

2.2 Laplacian Pyramid

Burt and Adelson [7] proposed Laplacian pyramid to achieving multiscale decomposition. The Laplacian pyramid decomposition at each step generates a lowpass (coarse) version of the original and the different (detail) version between the original and the prediction, resulting in a bandpass image (Figure 2). The process is then iterated on the coarse version. The Laplacian pyramid decomposition scheme is very like wavelet decomposition scheme. Wavelet decomposition is critically sampled, but at each Laplacian pyramid decomposition level generates only one bandpass image that does not have "scrambled". This frequency scrambling happens in the wavelet filter bank when a highpass channel, after down sampling, is folded back into the low frequency band, and thus its spectrum is reflected. In the Laplacian pyramid, this effect is avoided by down sampling the lowpass channel only.



(a)



(b)

Fig. 2. Laplacian Pyramid. (a) One level of the Laplacian pyramid decomposition. (b) One level of the Laplacian pyramid reconstruction.

2.3 Directional Filter Banks

Bamberger and Smith [8] proposed 2-D directional filter banks (DFB). The DFB is efficiently implemented via an l-level binary tree decomposition that leads to subbands with wedge-shaped frequency partitioning as shown in Figure 3. Minh and Vetterli [6] simplified DFB by two building blocks. The first building block is two-channel quincunx filter banks [9] with fan filters (see Figure 4) that split a 2-D spectrum into two directions: horizontal and vertical. The second building block are shearing operators, which amount to just reordering of image samples. Figure 5 shows an application of a shearing operator where a vertical edge becomes a 45° direction edge. By adding a pair of shearing operator and its inverse ("unshearing") to before and after, respectively, a two-channel filter bank in Figure 4, we obtain a different directional frequency splitting while maintaining perfect reconstruction. Thus, the key in the DFB is to use an appropriate combination of shearing operators together with two-direction splitting of quincunx filter banks at each node in a binary tree-structured filter bank, to obtain the desired 2-D spectrum division as shown in Figure 3.

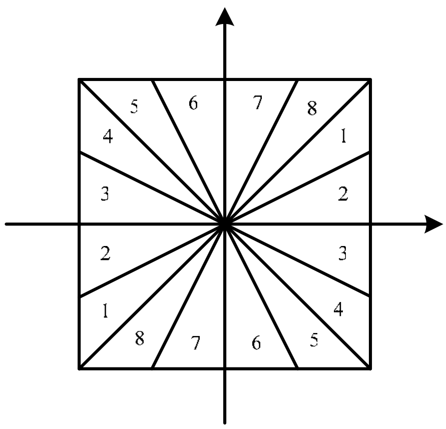


Fig. 3. The frequency partition of directional filter bank, where l=3 and there have 2^3=8 wedge-shaped frequency subbands.

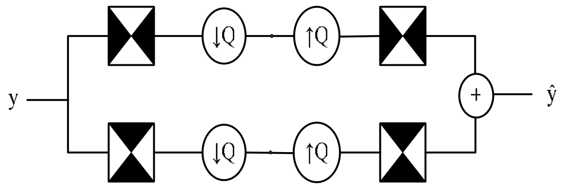


Fig. 4. 2-D spectrum splitting by quincunx filters banks.

where Q is a quincunx sampling matrix.

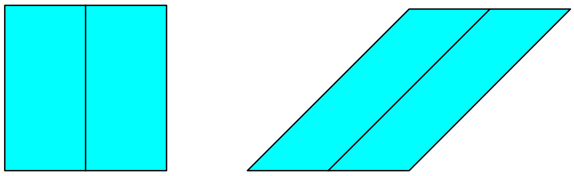


Fig. 5. Example of shearing operations in DFB decomposition. (a) Original image. (b) The original after shearing operation.

2.4 Pyramidal Directional Filter Banks

Figure 6 shows a multiscale and directional decomposition using a combination of a Laplacian pyramid (LP) and a directional filter bank (DFB). Bandpass images from the LP are fed into a DFB so that directional information can be captured. The scheme can be iterated on the coarse image. The combined result is a double iterated filter bank structure, named pyramidal directional filter bank (PDFB) [10] or discrete contourlet transform, which decomposes images into directional subbands at multiple scales.

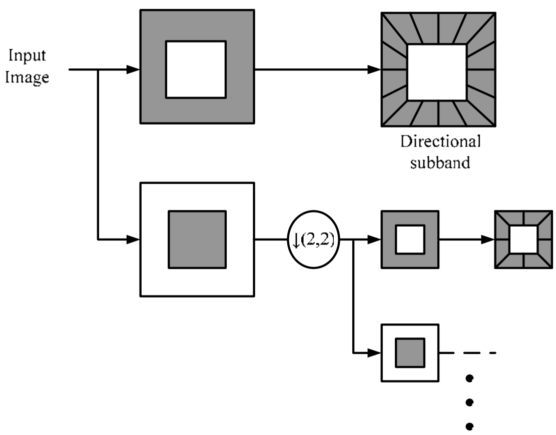


Fig. 6. Pyramid directional filter bank. A multiscale decomposition into octave subbands by the Laplacian pyramid and a directional filter bank is applied to each subband.

Since the multiscale and directional decomposition steps are decoupled in the PDFB or discrete contourlet transform, we can have a different number of directions at different scales, thus offering a flexible multiscale and directional expansion.

3. Speckle Reduction

Ultrasound imaging techniques are widely used in medical diagnosis. One of the limitations of ultrasound images is poor image quality affected by speckle noise. Speckle is a statistically complex phenomenon [11]. One source of speckle is interference of back-scattered signals, which in turn is caused by tissue inhomogeneity [12]. Other sources include the type of probe used (sampling frequency and quantization, etc), the part of the body imaged, and discontinuities in tissue caused by disease. Thus, speckle is usually the result of tissue ultrasound interaction, and not of noise originating at some external source, as it is the case with additive Gaussian noise [12]. One of the first statistical classifications of speckle noise was introduced in the area of laser scattering, where the noise was determined to follow a negative exponential distribution [13]. In synthetic aperture radar (SAR) images, speckle is often modeled as multiplicative noise following a Rayleigh distribution. Speckle in Ultrasound images has also been assumed to be multiplicative [14], following a Rayleigh distribution [12]. In another model for noise in SAR images, speckle approximately follows an additive Gaussian distribution after logarithmic transformation. In this paper, we apply Jain [1] speckle noise model for speckle reduction.

3.1 Speckle Noise Model

Jain [1] presented a kind of accurate and reliable model for speckle noise as:

$$f(x,y) = g(x,y) \cdot n_m(x,y) + n_a(x,y) \quad (1)$$

where g(x,y) is such as a noise-free original image, to be recovered, f(x,y) is a noisy observation of $g(x,y)$, $n_m(x,y)$ and $n_a(x,y)$ are multiplicative and additive noise respectively. Since the effect of additive noise (such as transducer noise) is considerably small compared to that of multiplicative noise (coherent interfering) in ultrasound system, that is $f(x,y) \cong g(x,y) \cdot n_m(x,y)$. (2)

To separate the noise from the original image, we take a logarithmic transform on both sides of (1) and rewrite the equation (2) as:

$$f'(x,y) = g'(x,y) + n'_m(x,y) \quad (3)$$

3.2 Speckle Reduction Algorithm

Figure 7 shown the block diagram of proposed speckle reduction algorithm.

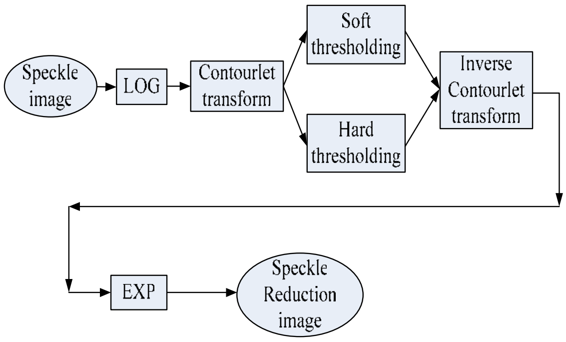


Fig. 7. Block diagram of the proposed speckle reduction algorithm.

Wavelet shrinkage methods, such as hard thresholding and soft thresholding, have been investigated for speckle reduction of images on a logarithmic scale. An advantage of soft thresholding is that it provides smoothness while hard thresholding preserves features. We apply soft thresholding at fine scales and hard thresholding at high scales to eliminate noise. The soft thresholding is defined by

$$U(f'(x,y)) = \begin{cases} sign(f'(x,y))(|f'(x,y)| - \lambda) & |f'(x,y)| > \lambda \\ 0 & |f'(x,y)| \le \lambda \end{cases} \quad (4)$$

In general, a threshold λ related to the noise level, orientation, and scale. Donoho's [2] uses a single global threshold. But noise coefficients under a contourlet transform have average decay through fine-to-coarse scales. Hence, we regulate soft thresholding by applying coefficient dependent thresholds at different scales.

The regulated threshold t_j^d can be computed through linearly decreasing function:

$$t_j^d = \begin{cases} [T_{\max} - \alpha(j-1)] \cdot \sigma_j^d & if \ T_{\max} - \alpha(j-1) > T_{\min} \\ T_{\min} \sigma_j^d & others \end{cases} \quad (5)$$

where σ_j^d is the standard deviation, j and d corresponding level and direction, respectively. α is a decreasing factor between two consecutive levels. $T_{\max}$, $T_{\min}$ are maximum and minimum value of σ_j^d , respectively. Figure 8 shows the regulated thresholds.

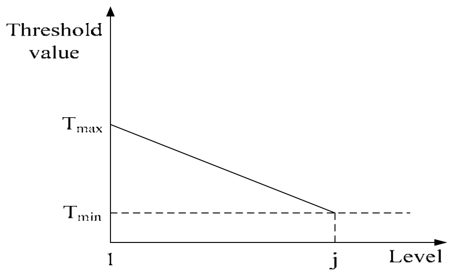


Fig. 8. A linear function of regulated thresholds.

Hard thresholding is defined by

$$U(f'(x,y)) = \begin{cases} f'(x,y) & |f'(x,y)| > \lambda \\ 0 & |f'(x,y)| \le \lambda. \end{cases} \quad (6)$$

The threshold λ was chosen as $\lambda = c\sigma^2$ where σ^2 is an estimate of the noise variance and c is a constant.

4. Experimental Results

The proposed speckle reduction algorithm was evaluated to 256 by 256 gray scale ultrasound images. To evaluate the performance of the proposed algorithm, a measurement SNR (signal to noise ratio) be used.

Figure 9(a) is a ROI of breast ultrasound image that have SNR 9.58. Figure 9(b) is the result of speckle reduction algorithm that has SNR 12.07. In the Laplacian Pyramid stage in the PDFB, we use the "9-7" biorthogonal filters. And in the DFB stage, we use the"23-45" biorthogonal quincunx filters designed by Phoong et al. [15].

5. Conclusions

In this paper, we presented a multiscale approach for speckle reduction. Speckle noise in ultrasound images has very complex statistical properties that depend on several factors. We applied the Jain's speckle noise model. Through a fine-to-coarse scale analysis of a speckled image on a logarithmic scale, distinct behaviors of noise can be differentiated. We took advantage of both soft and hard thresholding wavelet shrinkage techniques. The proposed methods significantly reduce the speckle while preserving the resolution and the structure of the original ultrasound images.

6. References

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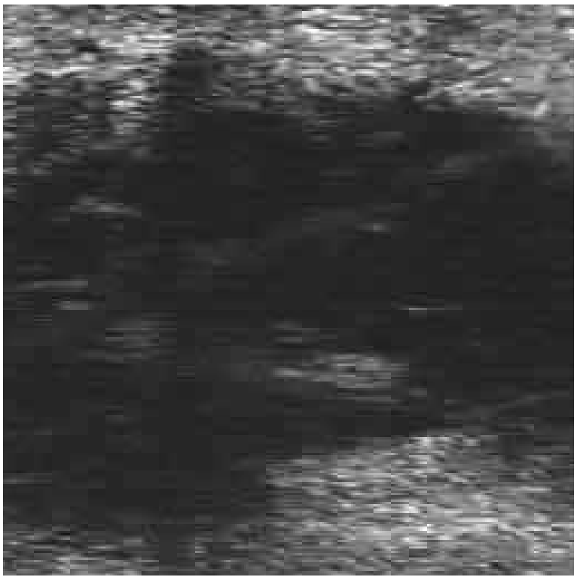
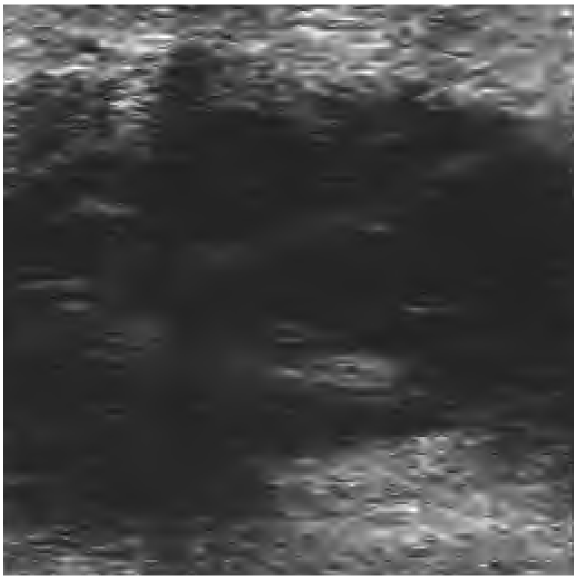


(a) speckle image



(b)Speckle reduction image

Fig. 9. Breast ultrasound tested image. (a) speckle image with SNR=9.58, (b) speckle reduction of (a) with SNR=12.07.