Ultrasound Images Denoising Based Context Awareness in Bandelet Domain

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Abstract. Ultrasound is widely used modalities in medical imaging. Ultrasound imaging is used in cardiology, obstetrics, gynecology, abdominal imaging, etc. Almost ultrasound image contains some noise, poor contrast. This paper describes a method to denoise ultrasound image based context awareness in bandelet domain. Our proposed method uses bandelet filters to remove noise in ultrasound images. For demonstrating the superiority of the proposed method, we have compared the results with the other recent methods available in literature.

Keywords: Bandelet · Denoising · Multilevel thresholding · Context-aware

1 Introduction

Almost every kind of ultrasound image data contains some noise. The noise has variability from one condition to other such as machine specification, detector specifications, surroundings, etc. The goal of denoising is to remove noise details from a given possibly corrupted ultrasound image while maintaining edges features. Many algorithms have been proposed for noise removal, but the recent trend to noise removal is use of wavelet transform [6–11] and some paper remove noise using curvelet, contourlet transform [12, 19, 22].

The discrete wavelet transform have serious disadvantages, such as shift-sensitivity [14] and poor directionality [15]. Several researchers have provided solutions for minimizing these disadvantages. Some of them have suggested stationary [16], cycle-spinning [13], shiftable [17], steerable [18] wavelet transforms, etc. By using a translation invariant wavelet as the first stage of the curvelet transform, Starck [12] used the curvelet transform for image denoising. A double filter banks structure, which be developed the contourlet transform, has used for denoising experiments by Do and Vetterli [13, 20]. The ridgelet transform is proposed by Donoho and Candes [21] to remove noise. However, the area of image denoising is hard work and still a great challenge.

In this paper, we have proposed a multilevel thresholding based context awareness technique for noise removal in bandelet domain. The proposed method has been

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compared with earlier denoising method using complex wavelet transform [5] and curvelet transform [12]. For performance measure, we used Peak Signal to Noise ratio (PSNR), Mean Square Error (MSE) and it has been shown that the present method yields far better results.

The rest of the paper is organized as follows: in Sect. 2, we described the basic concepts of bandelet transforms. Details of the proposed algorithm are given in Sect. 3. In Sect. 4, the results of the proposed method for denoising are shown and compared to other methods. Finally in Sect. 5, we presented our conclusions.

2 Principles of Bandelet Basis

The bandelet, was constructed by Le Pennec and Mallat [1, 3], have bring optimal approximation results for geometrically regular functions. Bandelets are adapted to geometric boundaries as an orthonormal basis. The bandelets is to perform a transform on functions defined as smooth functions on smoothly bounded domains [1]. As bandelet construction utilizes wavelets, many of the results follow. Similar approaches to take account of geometric structure were taken for contourlets and curvelets.

The bandelet is an orthogonal, multiscale transform [1, 2]. The bandelet decomposition is applied on orthogonal wavelet coefficients. It is computed with a geometric orthogonal transform. We consider a wavelet transform at a fixed scale 2^j. The wavelet coefficients $<f, \psi_{jn}>$ are samples of an underlying regularized function.

$$<f, \psi_{jn}> = f * \psi_j(2^j n) \quad \text{where} \quad \psi_j(x) = \frac{1}{2^j}\psi(-2^{-j}x)$$

The coefficients $\psi_v[n]$ are the coordinates of the bandelet function b_v € $L^2([0,1]^2)$ in the wavelet basis. A bandelet function [2] is defined by

$$b_v(x) = \sum_n \psi_v[n]\psi_{jn}(x)$$

It is a combination of wavelets and its support along a band as Fig. 1 [2]. Bandelets are as regular as the underlying wavelets. The support of bandelets overlap in the same way that the support of wavelets overlap [2]. This is particularly important for reconstructing image approximations with no artifacts. Figure 1 present a combination of wavelets along a band and its support is thus also along a band.

From an orthogonal wavelet basis with an orthogonal transformation, we are obtained from bandelets. Apply this transformation to each scale 2^j, an orthogonal basis of $L^2([0,1])^2$ defined as [2]:

$$B(T) \overset{def}{=} \underset{j \le 0}{U}\{b_v | \psi_v \in B(T_j)\} \quad \text{where} \quad T \overset{def}{=} \underset{j \le 0}{U} T_j$$

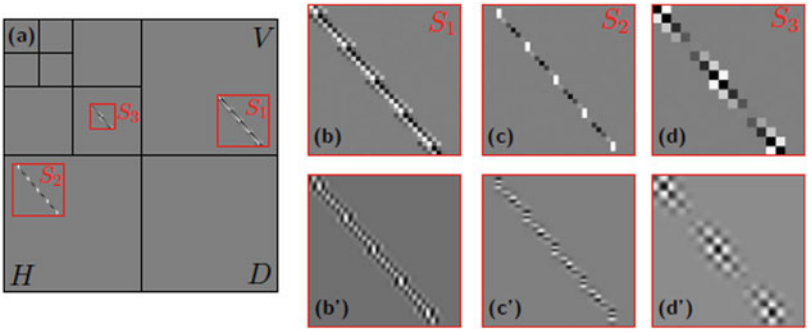


Fig. 1. (a) Localization on the wavelet domain of the squares S_i on which each Alpert wavelet vector is defined. (b)–(d) Discrete Alpert vectors ψ_{li} for various scales 2^l. (b')–(d') Corresponding bandelet functions (source: [2])

3 The Proposed Method

Denoising is the process of reducing the noise in the digital images that consists of three steps [4, 10, 12]: transform the noisy image to a new space. In new space, keep the coefficient where the signal to noise ratio is high, reduce the coefficient where the signal to noise ratio is low. A lot of work is available for the choice of suitable threshold in wavelet domain [4, 5, 7, 9]. Here, the proposed method is a two-part algorithm: bandelet coefficients computation and extraction of context aware bandelet filter.

3.1 Context-Based Soft-Thresholding Selection

The term 'context-aware', was first introduced by Schilit and Theimer [23], refer to context as location, identities of nearby people and objects, and changes to those objects.

Most of previous definitions of context are available in literature [27] that context-aware look at who's, where's, when's and what's of entities and use this information to determine why the situation is occurring. Here, our definition of context is:

"Context is any information that can be used to characterize the situation of an image such as: pixel, noise, strong edge, weak edge in medical image that is considered relevant to the interaction between pixels and pixels, including noise, weak and strong edge themselves."

In image processing, if a piece of information can be used to characterize the situation of a participant in an interaction, then that information is context. Contextual information can be stored in feature maps on themselves. Contextual information is collected over a large part of the image. These maps can encode high-level semantic features or low-level image features. The low-level features are image gradients, texture descriptors, shape descriptors information [24].

In this section, a wide range of soft-thresholding proposes to filter noise in ultrasound images. In the multiresolution analysis, the noise propagates at a higher level. For better removal of noise, especially the signal dependent noise, requires threshold at higher levels too. However, the threshold value should decrease, going from lower to higher levels. Filter-based technique features can independent of learning algorithm.

The bandelet coefficients correspond to signal of the image. The threshold T determines how the threshold is to be applied to the data. There are two popular: hard-thresholding and soft-thresholding. The soft-thresholding method shrinks all the coefficients towards the origin. The hard-thresholding shrinks only those coefficients to zero whose absolute value is less than *T* [25].

It is defined as:

$$w_{j^k}^{soft} = sign(w_{j^k}) \left(|w_{j^k}| - T \right)_+$$

where,

$$sign(w_{j^k}) = \begin{cases} +1, & if \quad w_{j^k} > 0 \\ 0, & if \quad w_{j^k} = 0 \\ -1, & if \quad w_{j^k} < 0 \end{cases}$$

and

$$(x)_+ = \begin{cases} x, & if \quad x \geq 0 \\ 0, & if \quad x < 0 \end{cases}$$

We estimate the threshold on the basis of statistical properties of bandelet coefficient. One of the estimates of standard deviation of noise (σ_n) in bandelet domain [25, 26] which depends on median of absolute bandelet coefficients is,

$$\widehat{\sigma_n} = Median(|w|)/0.6745$$

If $\{u_n\}$ are N independent Gaussian random variables of zero mean and variance σ^2, E (median $|u_n|_{0 \leq n \leq N}$) $\approx$ 0.6745 σ. This threshold gives good result on simulated data, but this model assumes noise to be Gaussian distributed. For better removal of noise, specially the signal dependent noise, thresholding should be done at higher levels. However the amount of shrinkage should decrease, moving from lower to higher levels. Here, the level-dependent threshold *T* is [26],

$$T = \frac{1}{2^{j-1}} \left(\frac{\sigma}{\mu} \right) M$$

where, *j* is number of level at which threshold is applied.

Suppose, we have given the denoised coefficients of the $(i-1)^{th}$ iteration step by $\widehat{X}^{i-1}[m,n]$, then the local variance of the i-th iteration step is given by [4]

$$\sigma_w^{(i)}[m,n]^2 = \frac{\sum_{j,k \in N} w_{j,k}^{(i)} \widehat{x}^{(i-1)}[j,k]^2}{\sum_{j,k \in N} w_{j,k}^{(i)}}$$

with a suitable set of weights $w^{(i)} = \{w_{j,k}^{(i)} | j, k \in N\}$. The adaptive thresholds of the i-th iteration step are define by

$$T^{(i)}[m,n] = \lambda^{(i)}(C)\sigma_n \frac{\sigma_n^2}{\sigma_w^{(i)}[m,n]^2}$$

For a coefficient-dependent of threshold, we propose a context-aware threshold selection. We use the local weighted variance $\sigma_w[m,n]^2$ of each bandelet coefficient $X^{(l,o)}[m,n]$ at level l using a window N, which covers a 4×4 neighborhood of $X^{(l,o)}[m,n]$ and a 2×2 neighborhood of the corresponding parent coefficient $X^{(l+1,o)}[m/2,n/2]$. Figure 2 shows one stage of the proposed context-based soft-thresholding.

3.2 Fast Bandelet Optimization

From a fast separable wavelet transform, we can be computed a fast discrete bandelet transform. We define a discrete warped wavelet transform which goes across the region boundaries. There are three steps associated to an image partition of the fast discrete bandelet transform [1]:

Firstly, we compute the image sample values in each region of the partition, we also describe its implementation together with the inverse resampling.

Secondly, a warped wavelet transform with a sub-band filtering along the flow lines is implemented. At the boundaries, warped wavelets still have two vanishing moments [1]. The wavelet coefficients of a discrete image are computed with a filter bank.

Finally, we compute bandelet coefficients along the flow lines. The transforming 1-D scaling functions into 1-D wavelets modifies a warped wavelet basis. From warped wavelet coefficients with a 1-D discrete wavelet transform along the geometric flow lines, we can compute bandelet coefficients.

The fast inverse bandelet transform includes the three inverse steps [1]:

(i) recovers the warped wavelet coefficient along the flow lines;
(ii) an inverse warped wavelet transform with an inverse sub-band filtering;
(iii) an inverse resampling which computes the image samples along the original grid from the samples along the flow lines in each region.

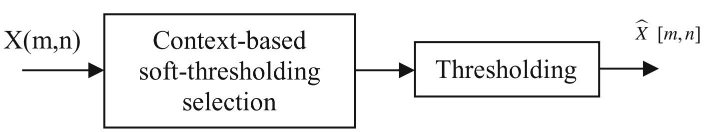


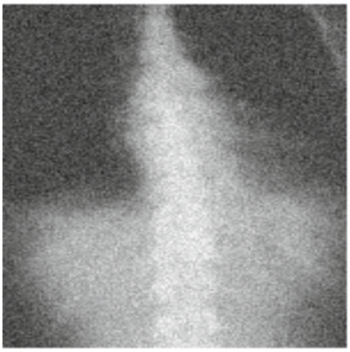
Fig. 2. Context-based soft-thresholding.

4 Experiments and Results

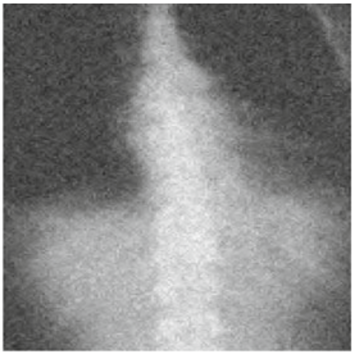
We applied the procedure described in Sect. 3 for our denoising experiments as briefly demonstrated in this section. For performance evaluation, we compare the proposed method based on context aware based bandelet (CABB) with the methods: the complex wavelet transform (CWT) based denoising [5], and the curvelet transform (CT) based denoising [12].

The comparison of results with other methods was done on our program and on the same images and at similar scale. The proposed method was tested using different noise levels of additive and multiplicative noise. We evaluated the performance of methods on PSNR and MSE values. MSE which requires two $M \times N$ gray-scale images, the original image I and the denoised image $\widetilde{I}$, is defined as,

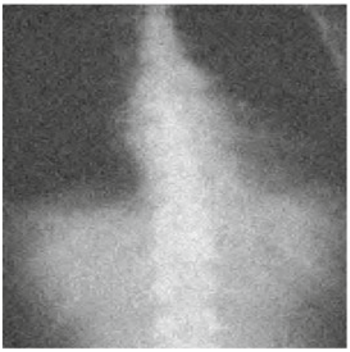
$$MSE = \frac{1}{MN} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left| I[m,n] - \widetilde{I}[m,n] \right|^2$$



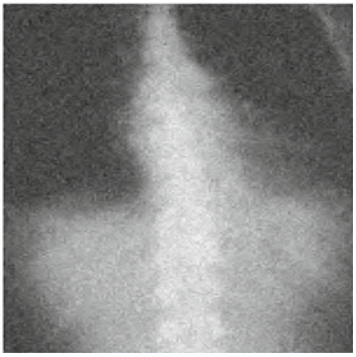
(a). Noisy image
(PSNR = 21.109dB)



(b). Denoised image by CWT method
(PSNR = 26.093 dB)

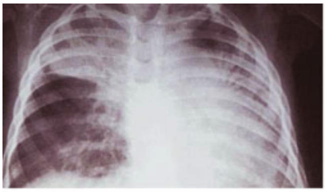


(c). Denoised image by CT
(PSNR = 29.145dB)

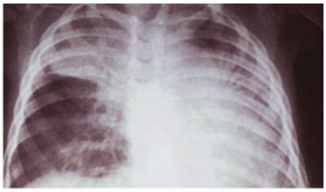


(d). Denoised image by the CABB
(PSNR = 30.583dB)

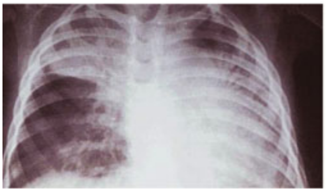
Fig. 3. Noisy image and denoised images by different methods.



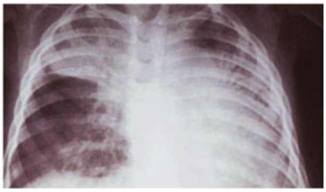
(a). Noisy image
(PSNR = 14.920 dB)



(b). Denoised image by CWT method
(PSNR = 15.415 dB)



(c). Denoised image by CT
(PSNR = 16.275 dB)



(d). Denoised image by the CABB
(PSNR = 16.838 dB)

Fig. 4. Noisy image and denoised images by different methods.

The PSNR is the most commonly used as a measure of quality of reconstruction in image denoising, defined as,

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

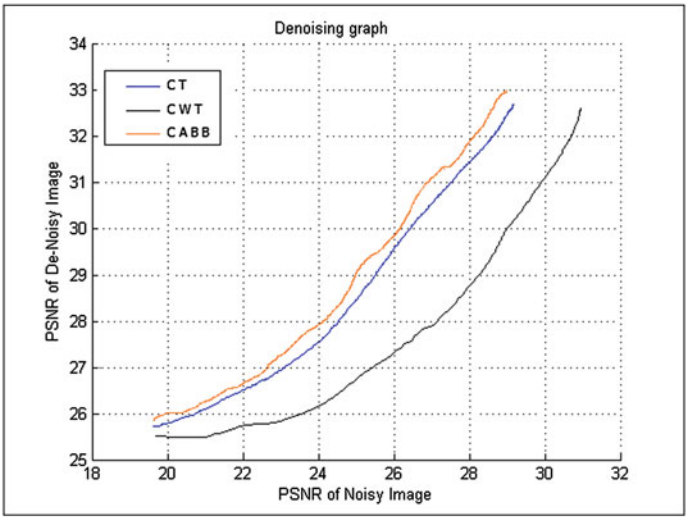


Fig. 5. Plot of PSNR values of denoised images using different methods.

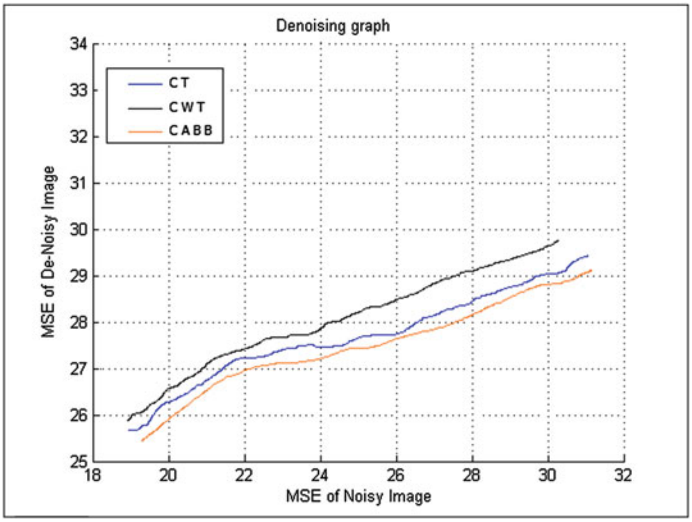


Fig. 6. Plot of MSE values of denoised images using different methods.

where, MAX_I is the maximum pixel value of the image.

Figures 3 and 4 show one representative noisy ultrasound image and denoised images by different methods as CABB, CWT and CT.

From Figs. 3 and 4, it is clear that the performance of the proposed method is better than other ones.

Figures 5 and 6 show the plot of PSNR and MSE values for different methods of the denoised images. In this figures, they can be well observed that the proposed method performs better than other methods.

To sum up, the proposed method performs better than the other methods of de-noising in complex wavelet and curvelet domain.

5 Conclusions

As the above presentation, ultrasound image are generally of poor contrast. For image denoising, almost of the previous methods are frequency filtering, frequency smoothing and wavelet transformation. That methods will be lots of information in medical image and lots of memory. This paper presents an adaptive technique context-based soft-thresholding for denoising in bandelet domain. It is clear that our proposed method performs better than the other methods. The bandelet transform apply the multiscale grouping to the set of coefficient. By performing context-based soft-thresholding the largest error of a denoised image is reduced resulting in lower energy of the error which gives better denoising result. In the future work, we design an intelligent framework to select soft-threshold for another medical image.

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