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Technical Note

Ripplet domain non-linear filtering for speckle reduction in ultrasound medical images

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ABSTRACT

Ultrasound imaging is one of the most important and cheapest instrument used for diagnostic purpose among the clinicians. Due to inherent limitations of acquisition methods and systems, ultrasound images are corrupted by the multiplicative speckle noise that degrades the quality and most importantly texture information present in the ultrasound image. In this paper, we proposed an algorithm based on a new multiscale geometric representation as discrete ripplet transform and non-linear bilateral filter in order to reduce the speckle noise in ultrasound images. Ripplet transform with their different features of anisotropy, localization, directionality and multiscale is employed to provide effective representation of the noisy coefficients of log transformed ultrasound images. Bilateral filter is applied to the approximation ripplet coefficients to improve the denoising efficiency and preserve the edge features effectively. The performance of the proposed method is evaluated by conductive extensive simulations using both synthetic speckled and real ultrasound images. Experiments show that the proposed method provides better results of removing the speckle and preserving the edges and image details as compared to several existing methods.

1. Introduction

The research in the medical imaging has produced many different imaging modalities for the clinical purpose. Among the different imaging modalities, ultrasound imaging is of a particular interest for medical diagnosis due to its cost effectiveness, portability, acceptability and safety [1]. However, ultrasound images are of relatively poor quality due to speckles (considered as multiplicative noise) present in them [2]. The presence of the speckle affects the human interpretation of the images as well as computer assisted methods. Furthermore, edge preserved speckle reduction and enhancement of the boundaries between different cavities and organs are of great need in ultrasound images. Thus, speckle reduction algorithms should be designed in such a manner that they suppress the speckle as much as possible without any significant loss of information.

Speckle reduction methods are classified in two categories viz. image averaging and image filtering [3]. Image averaging is usually achieved by averaging a series of uncorrelated ultrasound images from different viewpoints. However, these methods suffer from the loss of spatial resolution. Image filtering methods can be further classified as single scale spatial filtering such as linear [4], nonlinear adaptive methods [5,6], multiscale spatial filtering such as diffusion based methods [3,7–9] and others multiscale methods in different transform domain such as pyramid [10], wavelet [11], curvelet [12] and ridgelet [13] based methods which adopt the multiscale geometric analysis (MGA).

Currently lots of research works on image processing are concentrated in the transform domain. In that series, wavelet thresholding has been presented as a true signal estimation technique that utilizes the capabilities of wavelet transform (WT) for signal denoising [14–16]. The statistical methods such as nonlinear estimators based on Bayesian approach outperform the simple wavelet based thresholding [17]. Other despeckling techniques [15,18,19] based on Bayesian theory have been developed especially for the logarithmically transformed medical ultrasound images. In Ref. [20], wavelet based total variation filtering has been reported in which noisy image undergoes several iterations for suppressing the noise and leads to blurring effect. The WT based non-linear bilateral filter (NLBF) [21] provides better results of noise suppression and edge preservation [22]. It utilizes both the features of wavelet thresholding and bilateral filter. Wavelet transform is able to efficiently represent a function with one dimensional singularity [12,23]. However, it is less efficient in representing the sharp transition like line and curve singularities due to its limitation of direction.

To overcome this limitation, ridgelet transform has been proposed that is able to capture the line singularities of the images. However, it is unable to represent curve singularities effectively

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[13]. Donoho et al. have used curvelet transform to represent two dimensional singularities with the smooth curve [12]. The main idea of the curvelet is to represent a curve as a superposition of the functions of various lengths and widths obeying the scaling law. To represent the edges more efficiently in medical ultrasound images, Jun et al. [23] introduced a new MGA tool called ripplet transform type I which generalizes the curvelet transform with two additional parameters to achieve the anisotropy capability that guarantees to capture the singularities along the arbitrary shaped curves effectively. The ripplet transform overcomes the limitations of other transforms and also provides the sparse representation for the objects. Thus, in the present work, the discrete ripplet transform type I (DRT) is combined with non-linear bilateral filtering (NLBF) and thresholding scheme for speckle filtering in ultrasound images.

The paper is structured as follows. Section 2 presents the methodologies used for the proposed algorithm. Section 3 illustrates the proposed algorithm which is based on non-linear filtering in ripplet domain. To compare the performance of different methods, various experimental results are presented in Section 4 with qualitative and quantitative analysis. Conclusions are drawn in the final Section 5.

2. Methodology

2.1. Ripplet transform

The ripplet transform [23] is a higher dimensional generalization of the curvelet transform and is capable to represent the two dimensional signals at different scales and different directions. To achieve anisotropic directionality, curvelet transform uses a parabolic scaling law. From this perspective, the anisotropic properties of curvelet transform guarantees resolving two dimensional singularities along C^2 curves [12]. On the other hand, ripplet transform provides a new tight frame with a sparse representation for images with discontinuities along C^d curves [23].

If $d=1$, then ripplet does not show the anisotropy behavior. For $d=2$, it has the parabolic scaling same as the curvelets and for $d=3$, ripplet has the cubic scaling and so forth. Ripplet transform generalizes curvelet transform by adding two parameters, support c and degree d. Curvelet transform is just a special case of ripplet with $c=1$ and $d=2$. The anisotropic capabilities of ripplet transform type-1 are capable to efficiently represent the singularities along the arbitrary shaped curves due to these added new parameters c and d.

The continuous ripplet transform is defined as inner product of 2D integrable function $s(\vec{x})$ and ripplets $p_{a\vec{b}\theta}(\vec{x})$ as follows [23].

$$R(a, \vec{b}, \theta) = \langle s, p_{a\vec{b}\theta} \rangle = \int s(\vec{x})\overline{p_{a\vec{b}\theta}(\vec{x})}\, d\vec{x} \tag{1}$$

where $R(a, \vec{b}, \theta)$ is the ripplet coefficients and $\overline{(\cdot)}$ shows the conjugate operation. Ripplet function is defined as $p_{a\vec{b}\theta}(\vec{x}) = p_{a\vec{0}0}(R_\theta(\vec{x} - \vec{b}))$ and the element function of ripplet in frequency domain is given by,

$$\hat{p}_a(r, \omega) = \frac{1}{\sqrt{c}} a^{\frac{1+d}{2d}} W(a \cdot r) V\left(\frac{a^{1/d}}{c \cdot a} \cdot \omega\right) \tag{2}$$

where $\hat{p}_a(r, \omega)$ is the Fourier transform of ripplet element function $p_{a\vec{0}0}(\vec{x})$ in polar coordinate, $R_\theta = \begin{bmatrix} cos\theta & sin\theta \\ -sin\theta & cos\theta \end{bmatrix}$ is the rotation matrix, a, $\vec{b}$ and θ are the scale, position and rotation parameter, respectively. $W(r)$ and $V(\omega)$ represent the radial window and angular window, respectively which satisfy the two admissibility conditions [23].

$\int_{1/2}^{2} W^2(r)(dr/r) = 1$ and $\int_{-1}^{1} V^2(t)\,dt = 1$, These two windows divide the polar frequency domain into wedges shown in Fig. 1(a). The approximated image can be reproduced by the inverse of the ripplet transform [23].

$$s(\vec{x}) = \int R(a, \vec{b}, \theta) p_{a,\vec{b},\theta}(\vec{x}) da d\vec{b} d\theta / a^3 \tag{3}$$

2.1.1. Discrete ripplet transform

In the field of digital image processing, discrete transforms are needed. So discrete ripplet transform (DRT) are evaluated by discretizing the parameters of ripplets. The parameter a is sampled at dyadic intervals whereas $\vec{b}$ and θ are sampled at equal-spaced intervals. The scale parameter (a), the position parameter (b) and rotation parameter (θ) are substituted with a_j, $\vec{b}_k$ and θ_l, respectively which satisfy that $a_j = 2^{-j}$, $\vec{b}_k = [c \cdot 2^{-j} \cdot k_1,\ 2^{-j/d} \cdot k_2]^T$ and $\theta_l = (2\pi/c) \cdot (2^{-\lfloor j(1-1/d) \rfloor}) \cdot l$, where $\vec{k} = [k_1 k_2]^T$, $(\cdot)^T$ denotes the transpose of a vector and $j, k_1, k_2, l \in \mathbb{Z}$. The frequency response of ripplet function is given as [23]:

$$\hat{p}_j(r, \omega) = \frac{1}{\sqrt{c}} a^{(1+d/2d)} W(2^{-j} \cdot r) V\left(\frac{2^{-j(1/d-1)}}{c} \cdot \omega - l\right) \tag{4}$$

where W and V satisfy the following conditions

$$\sum_{j=0}^{\infty} \left| W(2^{-j} \cdot r) \right|^2 = 1 \quad \text{and} \quad \sum_{l=-\infty}^{\infty} \left| V\left(\frac{2^{-j(1/d-1)}}{c} \cdot \omega - l\right) \right|^2 = 1$$

For a fixed value of c, parameter d is used to control the resolution in the directions at each high pass band. For given a fixed value of d, parameter c controls the number of directions at all high pass bands. The c and d in combination are used to determine the final number of the directions at each band together. The discrete ripplet transform of the two dimensional signal $s(x,y)$ with size $\boldsymbol{M} \times \boldsymbol{N}$ is given by ripplet coefficients $R_{j,\vec{k},l}$.

$$R_{j,\vec{k},l} = \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} s(x, y) \overline{p_{j,\vec{k},l}(x, y)} \tag{5}$$

An approximated image $\hat{s}(x, y)$ can be reconstructed through inverse discrete ripplet transform

$$\hat{s}(x, y) = \sum_j \sum_{\vec{k}} \sum_l R_{j,\vec{k},l} p_{j,\vec{k},l}(x, y) \tag{6}$$

Fig. 1(b) and (c) shows a real ultrasound image and decomposition of the image processed with ripplet transform, respectively.

2.2. Bilateral filter

Bilateral filter is a non-linear filter performing the edge preserved denoising within the spatial domain [21]. Bilateral filter replaces the pixel values by a weighted sum of the pixels in a local neighborhood. It is achieved by the combination of two Gaussian filters, spatial (domain) and intensity (range) filter [22]. The range filter coefficients are proportional to the intensity distance $(s(y) - s(x))$ around the neighborhood of a pixel. The domain filter coefficients are proportional to the spatial distance $(y - x)$ of the pixel in approximation subband around its neighborhood. So at a pixel location x, the response of the NLBF can be computed as:

$$\hat{s}(x) = \frac{1}{h} \sum_{y \in N_s(x)} D_f(x, y) R_f(x, y) s(y) \tag{7}$$