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Despeckling of ultrasound medical images using nonlinear adaptive anisotropic diffusion in nonsubsampled shearlet domain

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ABSTRACT

Despeckling is of great interest in ultrasound medical images. The inherent limitations of acquisition techniques and systems introduce the speckles in ultrasound images. These speckles are the main factors that degrade the quality and most importantly texture information present in ultrasound images. Due to these speckles, experts may not be able to extract correct and useful information from the images. This paper presents an edge preserved despeckling approach that combines the nonsubsampled shearlet transform (NSST) with improved nonlinear diffusion equations. As a new image representation method with the different features of localization, directionality and multiscale, the NSST is utilized to provide the effective representation of the image coefficients. The anisotropic diffusion approach is applied to the noisy coarser NSST coefficients to improve the noise reduction efficiency and effectively preserves the edge features. In the diffusion process, an adaptive gray variance is also incorporated with the gradient information of eight connected neighboring pixels to preserve the edges, effectively. The performance of the proposed method is evaluated by conducting extensive simulations using both the standard test images and several ultrasound medical images. Experiments show that the proposed method provides an improvement not only in noise reduction but also in the preservation of more edges as compared to several existing methods.

1. Introduction

Currently, the research in medical imaging has produced many different imaging modalities for the clinical purpose. Among the different imaging modalities, ultrasound imaging is of a particular interest in the medical diagnosis of neck, chest, liver, abdominal cavity, gallbladder, pancreas, spleen, adrenal glands, kidney, prostate and scrotum due to its cost effectiveness, portability, acceptability and safety [1]. However, the ultrasound images are of relatively poor quality due to speckles (considered as a multiplicative noise) present in them. In addition to multiplicative noise, sometimes ultrasound (US) images also suffer from random additive Gaussian noise. The presence of speckles affects the human interpretation as well as accuracy of computer-assisted methods. Therefore, detection and enhancement of the boundaries between different cavities and organs are of great need in ultrasound images and is considered as a challenging problem. Sometimes, this process may suppress the important details of the ultrasound images. Thus, noise reduction algorithms should be designed in such a manner that they suppress the noise as much as possible without any significant loss of information presented in the US images.

Speckle reduction can be done in two categories viz. image averaging and image filtering methods [2]. Image averaging methods usually lead to the loss of spatial resolution. Filtering methods are practical alternative for most of the clinical applications. Furthermore, it can be classified as single scale spatial filtering such as linear [3,4], nonlinear, adaptive methods [4,5], multiscale spatial filtering such as diffusion based methods [2,6–8] and others multiscale methods in different transform domains such as pyramid [9], wavelet [10], ridgelet [11] and curvelet [12]. Simple mathematical linear filters such as mean filter degrade the sharp transitions (line and edges) of the image [4]. Most popular nonlinear filters such as median filter are employed to all the pixels whether they are corrupted or not. The weighted median filter is also used for the noise reduction. It is able to retain more edges than the classical median filter [5]. However, there is a loss of resolution by suppressing the fine details. In the category of multiscale spatial filtering, partial differential equations (PDE) are used to implement some filters for denoising purpose. The most popular methods include Lee filter [13], Kuan method [14] and anisotropic diffusion equations proposed by Perona and Malik [6]. So it is called P–M equations that

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provide a method for image smoothing. A lot of work has been done with anisotropic diffusion equations in such a way that the important structural information can be retained in the denoised images [8,15–17]. Besides the diffusion methods, various multiscale methods have been employed for noise reduction [10,12,18–21].

Currently, lots of research work on image processing is concentrated in the transform domain. In that series, wavelet thresholding has been presented as a true signal estimation technique that exploits the capabilities of wavelet transform (WT) for signal denoising [18,19]. The main strength of wavelet thresholding is its capability to process the different frequency components of an image, separately [22]. Thus, many efforts have been made to suppress the different types of noise and to overcome the limitations of spatial domain filtering by wavelet thresholding methods [19–21]. However, it may lead to the formation of some visual artifacts around sharp discontinuities. The WT is able to efficiently represent a function with one dimensional singularity. However, it is less efficient in reflecting the sharp transitions such as line and curve singularities due to its limitation of direction [23]. To overcome this limitation, ridgelet transform has been proposed to provide the information about the orientation of the linear edges [11]. However, it does not represent the two dimensional singularities. Donoho et al. [12] has presented curvelet transform (CT) used to represent two dimensional singularities with the smooth curve and provides better denoising and edge preservation results. Contourlet transform proposed by Vetterli et al. [24] performs well in noise reduction due to application of multiscale Laplacian pyramid (LP) followed by directional filter banks. However, it has less directional features than curvelets. To represent the edges more efficiently, Labate et al. introduced a new multiscale analysis tool called shearlet that has all properties like other MGA tools as multiscale, localization, anisotropy and directionality [25,26]. The decomposition of the shearlet transforms (ST) consists of multiscale and multidirectional decomposition that are similar to contourlets except that there is no limitation on the number of directions. Shearlets can also be constructed in discrete domain realized by combination of the Laplacian pyramid (LP) and directional filters, but still the lack of shift invariance problem cannot be overcome. Easley et al. [27] proposed nonsubsampled shearlet transform (NSST) that is realized by nonsubsampled Laplacian pyramid (NSLP) and several shearing filters. The NSST also provides the flexible directional selectivity and shift invariance [27,28]. Based on the above concept, the present work combines the NSST with improved nonlinear diffusion equations and thresholding scheme for despeckling of the US medical images.

The paper is structured as follows. Section 2 presents the methodologies used for the proposed method. Section 3 illustrates the implementation steps of the proposed despeckling algorithm. In Section 4, various experimental results are discussed and compared with the several other methods in terms of the different performance measures. Conclusions are drawn in Section 5.

2. Methodology

2.1. Anisotropic diffusion

Anisotropic diffusion is modeled by Perona and Malik for defining a scale space image [6]. This model is an extension of the heat equation that is based on the partial differential equation (PDE). Let $s(x, y; t)$ is an image with coordinates (x, y) at time t, and then the continuous anisotropic diffusion is defined as

$$\frac{\partial s(x, y; t)}{\partial t} = div[g(x, y; t)\nabla s(x, y; t)] \tag{1}$$

where *div* is the divergence operator, g is the diffusion coefficient and ∇ is a gradient operator with respect to space variables. The diffusion model becomes isotropic, if g is a constant parameter. When g is a function of directional parameters, the diffusion model becomes anisotropic. Perona–Malik (PM) suggested the two well known diffusion coefficients defined as,

$$g(f) = \frac{1}{1 + \left(\frac{f}{\lambda}\right)^2} \tag{2a}$$

$$g(f) = \exp\left[-\left(\frac{f}{\lambda}\right)^2\right] \tag{2b}$$

where $f = |\nabla s|$ and the parameter λ serves as a threshold of gradient size. A smaller gradient is diffused, while positioning a larger gradient is treated as edges. Instead of having many computational and theoretical properties, there is one serious problem with the diffusion method. It is very sensitive to the noise which may introduce large oscillations of the gradient. Furthermore, the PM method cannot differentiate between true edges and noises. Another problem is the stair casing effects that arise around the smooth edges [29]. To provide the solution of this problem, Catte et al. [30] proposed that a Gaussian kernel G_σ is convolved with the images to reduce the effect of noise and provide better estimation of the local gradient. However, it is very sensitive to the number of diffusion iteration by considering only the gradient information of the pixel. Normally, large gradient values are treated as edges, but sometimes the important details along with edges available in the image may have low gradient magnitude [17]. Therefore, the gray level variance is incorporated along with the gradient of the pixels to evaluate the diffusion coefficients. In the PM method, the derivative term (∇s) is calculated using a template of four closest neighbors of a pixel (x, y). This term can be evaluated more accurately by considering the large number of the neighboring pixels within a template and the corresponding algorithm improves the quality of the images. Moreover in this work, eight nearest neighboring pixels are used within 3×3 template to evaluate the gradient term and the adaptive gray variance is also included along with the gradient to estimate the diffusion coefficients.

2.2. Nonsubsampled shearlet transform

The NSST is an extension of the WT in multidimensional and multidirectional case which combines the multiscale and direction analysis, separately. Firstly, the NSLP is used to decompose an image into low and high-frequency components, and then direction filtering is employed to get the different subbands and different direction shearlet coefficients. Direction filtering is achieved using the shear matrix which provides many more directions. The introduction of the NSST is given as follows:

Consider a two-dimensional affine system with composite dilations as [27,28]

$$A_{DS} = \left\{\psi_{j,k,m}(x) = |\det D|^{j/2}\psi(S^k D^j x - m) : j, k \in \mathbb{Z}, m \in \mathbb{Z}^2\right\} \tag{3}$$

where D refers to the anisotropic matrix, S denotes the shear matrix and j, k and m are scale, direction and shift parameter, respectively. The D and S are both 2×2 invertible matrices and $|\det S| = 1$, the elements of the system are called composite wavelet, if it forms a Parseval frame for $L^2(\mathbb{R}^2)$, which is also an affine like system. For any $f \in L^2(\mathbb{R}^2)$

$$\sum_{j,k,m}\left|\langle f, \psi_{j,k,m}\rangle\right|^2 = \|f\|^2 \tag{4}$$

The anisotropic dilation matrix $\begin{bmatrix} d & 0 \\ 0 & d^{1/2} \end{bmatrix}$ or $\begin{bmatrix} d^{1/2} & 0 \\ 0 & d \end{bmatrix}$ where $d > 0$ controls the scale of shearlets, which ensures that the frequency support of shearlets becomes increasingly stretched at finer