https://doi.org/10.2352/ISSN.2470-1173.2019.11.IPAS-252

Patch-based Image Despeckling using Low-rank Hankel Matrix Approach with Speckle Level Estimation

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Abstract

In this study, we propose an image despeckling method based on low-rank Hankel matrix approach and speckle level estimation. Annihilating filter-based low-rank Hankel matrix, so called ALOHA approach is very useful to various areas, such as image inpainting and impulse noise reduction. The proposed method utilizes this approach because it provides high performance in completing irregularly subsampled images. Speckled image are subsampled using patch-based speckle level estimator which selects pixels with low speckle level and abandon the others. The subsampled image is reconstructed using low-rank structured matrix completion. Our experimental results demonstrate that precisely estimated speckle level improves despeckling performance significantly. The accuracy of the proposed speckle estimator validates better despeckling performance of the proposed method compared with conventional despeckling methods.

Introduction

Speckle noise is a type of acoustic phenomenon responsible for the granular appearance [1]. Images obtained from surfaces with rough wavelength by coherent imaging systems using laser, synthetic aperture radar (SAR), and ultrasound suffer from this phenomenon. When an image is corrupted by this granular pattern as shown in Fig. 1, the contrast and detailed texture of the image is severely distorted. This distortion degrades the performance of image processing techniques such as object detection, segmentation and classification. The quality of image gained by imaging system is also hampered by speckle noise. Ultrasound image, for example, are widely used for medical diagnostics. Speckled image hinders physician diagnosing patients precisely because physicians are hard to recognize anatomical structure.

Over the years, a number of approaches to suppress speckle noise, so called despeckling, have been introduced. In a very early stage, primitive filter such as mean and median filter were introduced [2, 3]. However, these methods had limitations because of severe artifacts on the edges. To overcome this drawback, adaptive filters were proposed by several authors [4, 5]. Using local statistics, adaptive filters could suppress speckle noise efficiently and preserve edge properties of the image simultaneously. Other authors introduced wavelet-based noise suppression method. Wavelet-based despeckling method decomposes complex statistics of speckled image into simple multiscale domain. Hard thresholding or soft thresholding is usually applied to the detailed wavelet coefficients of noisy images [6]. Time-invariant transform, such as stationary wavelet transform (SWT) [7] and dyadic wavelet transform (DWT) [8], was used to denoise. Anisotropic diffusion filters have been also well-known approach in despeckling area [9]. They aimed toward the suppression of noise while preserving boundaries between object

(a) (b)

Figure 1. *(a) Original image (b) Degraded image.*

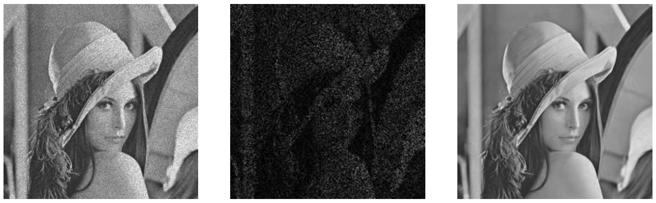
structures, especially anatomic structure in ultrasonic images. Diffusion is known as the process that equilibrates concentration differences by distribution particles from areas with high to areas with low concentration. This diffusion filter is controlled by a partial differential equation, encouraging noise suppression being occurred within homogeneous regions instead of across edges.

In the conventional methods, severe speckle noise could be propagated to whole image. This error propagation could be prevented by estimating speckle noise level. The artifact of despeckled image is reduced if the image is reconstructed from pixel with low speckle noise level. J. Seabra *et al.* [10] introduced speckle isolation method to estimate speckle components from the ultrasound data with the purpose of tissue characterization.

Annihilating filter-based low-rank Hankel matrix approach, so called ALOHA, was proposed as powerful inpainting technique. Image inpainting problem is converted into a low-rank structured matrix completion problem because annihilation property results in a low-rank block Hankel structure data matrix [11]. This approach was applied for impulse noise reduction problem with observation that considers impulse noise as sparse component of image. For further information, refer to [11].

Image despeckling could be treated as image reconstruction from sparse component with random position if speckle noise level estimation is combined. Using ALOHA algorithm, whole image is not required for image reconstruction. Image corrupted with speckle noise is masked by speckle noise estimation. The masked image has only sparse component but low speckle noise level. Despeckled image is obtained by completing masked image using ALOHA algorithm. Figure 2 (b) is a masked image when speckle noise level is known. In this case, pixel with high speckle noise level in Fig. 2 (a) is abandoned, so only sparse but relatively accurate information remains. As shown in Fig. 2 (c), the very competitive despeckling results were obtained by ideally formed mask and ALOHA. Detailed experimental results are provided in Section 4.

In this paper, patch-based image despeckling using low-rank Hankel matrix approach with speckle level estimation is proposed.



(a) (b) (c)

Figure 2. *(a) Image degraded by speckle noise* ($\sigma = 0.037$) *(b) Masked image in known speckle noise level (c) Despeckling result.*

First, the speckle noise is estimated using local statistics. Then, pixel with high speckle noise level is abandoned and despeckled image is obtained by low-rank Hankel matrix completion. The rest of this paper is organized as follows. In Section 2, the proposed overall algorithm is explained. Experimental results including comparisons with conventional method are shown in Section 3. In Section 4, finally, we conclude the paper.

Proposed Method

The proposed method begins with noise estimation using local statistics. Based on estimated speckle noise level, sparsely masked image is obtained. The masked image is inpainted with ALOHA algorithm in [11]. Finally, the despeckled image is achieved by brightness compensation.

Noise estimation

Consider an image $\mathbf{x}$ degraded by speckle noise $\mathbf{v}$. The speckle noise is signal-dependent noise, an observed image $\mathbf{z}$ will be

$$\mathbf{z} = \mathbf{x}\mathbf{v}. \tag{1}$$

where $\mathbf{E}(\mathbf{v}) = \mathbf{1}$ and $\mathbf{Var}(\mathbf{v}) = \boldsymbol{\sigma}_{\mathbf{v}}^{2}$.

The exact speckle noise level could be calculated as division of $\mathbf{z}$ and $\mathbf{x}$ if an image $\mathbf{x}$ is known. However, the despeckled image could not be known surely, so roughly despeckled image replaces $\mathbf{x}$ as the reference image. In this study, we apply log-transform and local mean filtering to the degraded image. The logarithmic transformation converts Eq. (1) into

$$\mathbf{Z} = \mathbf{X} + \mathbf{V}, \tag{2}$$

$$\mathbf{Z} = \mathbf{log}(\mathbf{z}),\ \mathbf{X} = \mathbf{log}(\mathbf{x}),\ \text{ and } \mathbf{V} = \mathbf{log}(\mathbf{v}).$$

This transformation allows utilizing traditional denoising algorithm because multiplicative and signal-dependent noise model is turned into additive and signal-independent noise model. From observed image $\mathbf{Z}$, the reference image $\widehat{\mathbf{X}}$ could be obtained by local mean filtering,

$$\widehat{\mathbf{X}}(\boldsymbol{m},\boldsymbol{n}) = \frac{\mathbf{1}}{\mathbf{N}^2}\sum_{[\boldsymbol{i},\boldsymbol{j}]\in \boldsymbol{W}} \mathbf{Z}(\boldsymbol{i},\boldsymbol{j}). \tag{3}$$

where $\boldsymbol{W}$ is $\mathbf{N} \times \mathbf{N}$ local window. Replacing $\mathbf{X}$ by $\widehat{\mathbf{X}}$ could yield the speckle noise level estimation,

$$\overline{\mathbf{V}} = \mathbf{Z} - \widehat{\mathbf{X}}, \tag{4}$$

or

$$\overline{\mathbf{V}} = \left|\mathbf{Z} - \widehat{\mathbf{X}}\right|. \tag{5}$$

where $\overline{\mathbf{V}}$ is an estimated speckle noise level.

If the noise is perfectly estimated, noise estimation model (5) holds because noise with same absolute value should be treated equally. However, in practical case, noise estimation model (4) holds because noise estimation is not accurate. This inaccuracy affects constructing masked image like Fig. 2 (b) because choosing pixel with positive speckle noise level instead negative level could yield more artifacts. Comparison between noise estimation model (4) and (5) is presented in Section 4.

Brightness compensation

Noise estimation model (4) has less artifact compared with model (5) but collecting pixel with negative speckle noise level does not preserve brightness of original image. From Eq. (1), $\mathbf{E}(\mathbf{z}) = \mathbf{E}(\mathbf{x})$ holds because $\mathbf{E}(\mathbf{v}) = \mathbf{1}$. Brightness of despeckled image is compensated by

$$\tilde{\mathbf{x}}_{\boldsymbol{c}} = \tilde{\mathbf{x}} \cdot \frac{\mathbf{E}(\mathbf{z})}{\mathbf{E}(\tilde{\mathbf{x}})}, \tag{6}$$

where $\tilde{\mathbf{x}}$ is the despeckled image before brightness compensation and $\tilde{\mathbf{x}}_{\boldsymbol{c}}$ is final despeckled image after brightness compensation.

Experimental Results

The performance of the proposed method was compared with three conventional methods, Lee[4], SRAD[9], and DPAD[12]. Lena image (512×512) with $\sigma_{\mathrm{v}} = 0.037$ noise shown in Fig. 1 (b) is used for the objective evaluation of the proposed method. For noise estimation, 3×3 local window is used. Based on the noise estimation result, pixel less affected by speckle noise is selected for constructing masked image shown in Fig. 2 (b). In our experiment, 15% of pixel is collect from corrupted image.

In this study, we evaluated performance of the proposed method with and without speckle noise estimation. Without speckle noise estimation, we assumed the case that speckle noise is known exactly. This case shows maximum performance of proposed method if speckle noise is perfectly estimated. On the other case, speckle noise level is unknown and estimated by proposed estimator.

Comparison between noise estimation model (4) and (5) is given in Fig. 3. As shown in Fig. 3 (c) and (d), the proposed method with noise estimation model (4) has less artifact compared with (5). Since speckle noise is signal-dependent noise, error propagation is more significant if positive speckle noise is mischosen.

For the quantitative comparison, we used evaluation index such as the peak signal-to-noise ratio (PSNR), Structural Similarity (SSIM), and Figure of Merit (FoM). Compared with the conventional methods, our proposed method shows better PSNR, SSIM, and FoM value when speckle noise level is known. The proposed method with speckle noise estimation shows better FoM value compared with conventional methods.

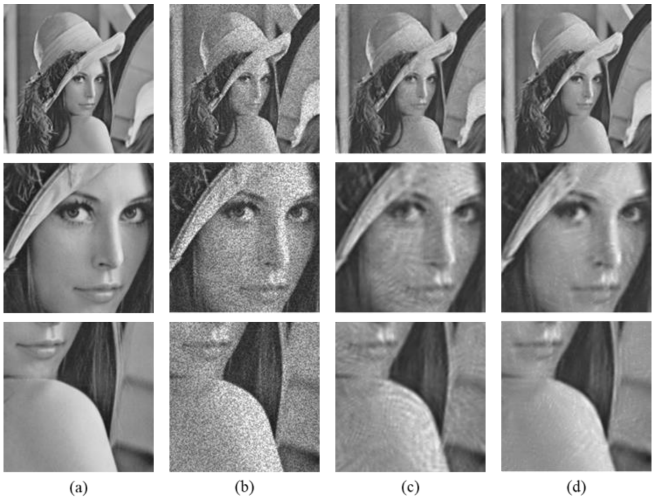


Figure 3*. Noise estimation model comparison: (a) Original image (b) Image degraded by speckle noise with variance 0.037 (c) Proposed method (unknown) with noise estimation model (5) (d) Proposed method (unknown) with noise estimation model (4).*

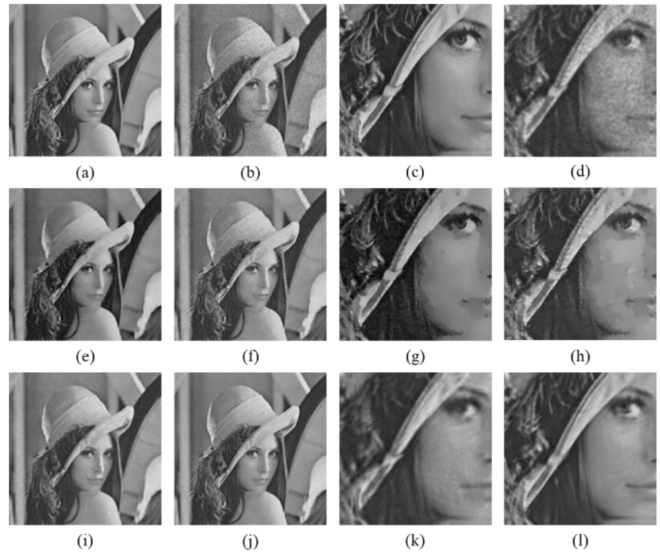


Figure 4*. Experimental results: (a), (c) Original image, (b), (d) Lee, (e), (g) SRAD, (f), (h) DPAD, (i), (k) Proposed method (unknown), (j), (l) Proposed method (known).*

Comparison of PSNR, SSIM and FoM values for conventional method and the proposed method

Method	PSNR (dB)	SSIM	FoM
Lee [4]	27.49	0.3816	49.88
SRAD [9]	24.15	0.4152	83.78
DPAD [12]	29.06	0.4417	82.40
Proposed (known)	30.36	0.5322	89.22
Proposed (unknown)	27.86	0.4070	84.39

In the qualitative evaluation, our proposed method has superiority compared with conventional methods. In proposed method, the artifact in low frequency region is significantly decreased and the lump texture in diffusion method does not appear as shown in Fig 4.

Conclusions

In this study, image despeckling method using Low-rank Hankel matrix approach with speckle noise estimation is proposed. Using the logarithmic transformation and local statistics, speckle noise level is estimated from observed image. Based on estimated speckle noise level, masked image is constructed and despeckled image is obtained using Annihilating filter-based low-rank Hankel matrix approach. The proposed method demonstrated enhanced performance both quantitatively and qualitatively comparing with the conventional methods.

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