

Speckle reduction algorithm for laser underwater image based on curvelet transform

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Based on the analysis on the statistical model of speckle noise in laser underwater image, a novel speckle reduction algorithm using curvelet transform is proposed. Logarithmic transform is performed to transform the original multiplicative speckle noise into additive noise. An improved hard thresholding algorithm is applied in curvelet transform domain. The classical Monte-Carlo method is adopted to estimate the statistics of contourlet coefficients for speckle noise, thus determining the optimal threshold set. To further improve the visual quality of despeckling laser image, the cycle spinning technique is also utilized. Experimental results show that the proposed algorithm can achieve better performance than classical wavelet method and maintain more detail information.

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Active laser imaging system (ALIS) is a highly effective sensing instrument. For the ability of obtaining two-dimensional (2D) images with high resolution, ALIS has been widely used in numerous military and civil applications, especially for underwater target detection and recognition. Laser underwater image can provide much more target information than the one-dimensional (1D) signal obtained by conventional sonar system^[1]. However, as a coherent signal, the laser wave reflected from different positions of the object surface will definitely generate interference, thus causing the so-called speckle noise phenomenon. On the other hand, water is a highly complicated medium, absorption, forward and backward scattering in water can also bring serious speckle noises in laser image. Speckle noises will bring degradation in image contents, thus making following segmentation, analysis, and interpretation tasks more difficult.

So far, wavelet has been emerging as an effective solution for speckle reduction in laser image; numerous wavelet based algorithms have been developed. Wavelet is an optimal tool for 1D piecewise smooth signals, however, it has serious limitations in dealing with high dimensional signal like images. As a tense-product of 1D wavelet, 2D separable wavelet is only good at isolating the discontinuities at edge points, but cannot detect the smoothness along the edges. On the other hand, 2D wavelet decomposes image in only three directional subbands, which means that it can only capture limited directional information. Therefore, wavelet based speckle reduction algorithms can not always obtain good speckle reduction results, especially for preserving sharp features and the resulted visual artifacts.

In 1999, Candes and Donoho developed a novel multiscale geometric analysis tool-curvelet^[2]. To overcome the disadvantages of wavelet, the idea of curvelet is to effectively represent the curves in natural image as superposition of functions of various lengths and widths. It is implemented by combining multiscale ridgelet with spatial bandpass filtering. Figure 1 illustrates the structure of the curvelet transform.

In the first stage of curvelet transform, the “à trous”

algorithm is utilized to the original image for bandpass filtering to isolate different scales. This step can kill all multiscale ridgelets which are not in the frequency range of the filter. The “à trous” algorithm decomposes an input image I into $J + 1$ subbands as a superposition of the following form

$$I(x, y) = c_J(x, y) + \sum_{j=1}^J w_j(x, y), \quad (1)$$

where c_J is a coarse version of the original image I , w_j represents the detail subbands of different scales. The bandpass filtering is set so that the curvelet length and width at fine scales obey the scaling law $\text{width} \approx \text{length}^2$.

Since linear structures occur at a wide range of scales, the subbands w_j are then analyzed by the local ridgelet transform (LRT). At each fixed scale, w_j is decomposed into smoothly overlapping blocks to avoid blocking artifacts. After renormalization and transportation at all scales and locations, ridgelet transform is taken for the smoothly localized data, thus obtaining the final curvelet coefficients.

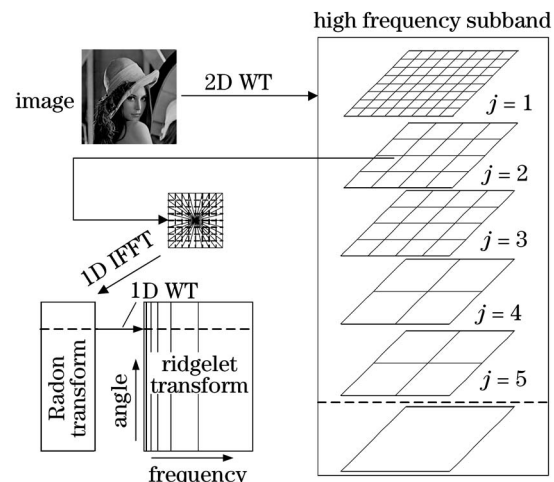


Fig. 1. Flow graph of curvelet transform.

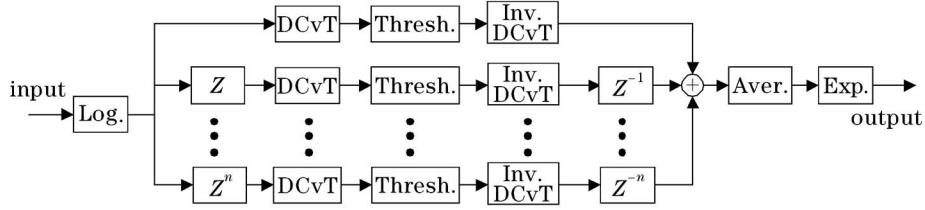


Fig. 2. Block structure of the proposed speckle reduction algorithm.

Given $a > 0$, $b \in R$, and $\theta \in (0, 2\pi]$, $\psi(\cdot)$ denotes a wavelet function, the bivariate ridgelet function is

$$\psi_{a,b,\theta}(x, y) = a^{-1/2} \cdot g\psi((x \cos \theta + y \sin \theta - b)/a). \quad (2)$$

The ridgelet decomposition value for image $f(x, y)$ can be expressed as

$$R_f(a, b, \theta) = \int \int \bar{\psi}_{a,b,\theta}(x, y) f(x, y) dx dy, \quad (3)$$

where $\bar{\psi}$ denotes the conjugate of ψ . The reconstruction formula is achieved by

$$f(x) = \int_0^{2\pi} \int_{-\infty}^{+\infty} \int_0^{+\infty} R_f(a, b, \theta) \psi_{a,b,\theta}(x) \frac{da}{a^3} db \frac{d\theta}{4\pi}. \quad (4)$$

A ridgelet is constant along lines $x \cos \theta + y \sin \theta = \text{const}$, transverse to these ridges, it is a wavelet. So ridgelet can be implemented as the application of 1D wavelet transform to the slice of the Radon transform.

Based on curvelet transform, we proposed a novel speckle reduction algorithm for underwater laser image. It includes the following steps: logarithmic transform, cycle-spinning, digital curvelet transform (DCvT), thresholding, inverse curvelet transform, inverse cycle-spinning, and post processing. Figure 2 depicts an overview of the proposed speckle reduction algorithm.

The speckle phenomenon in laser imaging system can be seen as the multiplicative noise with statistical property of negative exponent^[3], which is

$$I = I_0 \times I_s, \quad (5)$$

$$p_{I_s}(I_s) = \langle I_s \rangle^{-1} \exp[-I_s / \langle I_s \rangle], \quad (6)$$

where I is the final signal intensity, I_0 represents the ideal signal without speckle noise, I_s is the action parameter of speckle noise, $\langle \cdot \rangle$ denotes the average operation. If the object surface is nearly smooth, that is, $I_0(x, y)$ is approximately constant, the standard variances of speckle noise at each pixel are always equal, and a linear relation exists between variance of the final signal and speckle noise

$$\text{Var}(I_s) = \text{Var}(I) / \langle I \rangle^2. \quad (7)$$

Since the additive white Gaussian noise (AWGN) occurs with the highest probability in real imaging and sensing systems, a logarithmic transform is firstly performed to convert the multiplicative speckle noise into an additive noise before speckle processing, which can be represented as

$$\tilde{I}(x, y) = \tilde{I}_0(x, y) + \tilde{\epsilon}(x, y), \quad (8)$$

where $\tilde{I}(x, y) = \ln(I(x, y))$, $\tilde{I}_0(x, y) = \ln(I_0(x, y))$, $\tilde{\epsilon}(x, y) = \ln(I_s(x, y))$.

Curvelet transform can be treated as a linear transform, so the speckle noise is still additive after being transformed into curvelet domain, which is

$$\text{DCvT}(\tilde{I}) = \text{DCvT}(\tilde{I}_0) + \text{DCvT}(\tilde{\epsilon}). \quad (9)$$

For the multiresolution, directionality, localization and isotropy properties of curvelet transform, speckle noise can be perfectly separated from original image in the curvelet domain. Speckle noises in laser images will generate significant wavelet coefficients just like edges and curves, but there is less likely to generate significant curvelet coefficients. Therefore good speckle reduction results can be achieved by the simple hard thresholding method in the curvelet domain. The idea of thresholding operation is to cut off all coefficients below the threshold, so the key problem is to choose an appropriate threshold. Donoho *et al.* proved that $T = \sigma \sqrt{2 \log(n)/n}$ is optimal for the zero-mean Gaussian noise in wavelet domain^[4,5]. However, we found that this definition does not work well for curvelet transform. In our despeckling algorithm, a hard thresholding method with improved threshold selection is introduced to be

$$\Theta(x) = \begin{cases} w(j, k) & |w(j, k)| > T(j) \\ 0 & |w(j, k)| \leq T(j) \end{cases}, \quad (10)$$

where $w(j, k)$ is the curvelet transform coefficients of $\tilde{I}(x, y)$, j and k denote decomposition scale and coefficient position, respectively. $T(j)$, $j = 1, \dots, N$, is a predefined threshold set. For the lowest frequency subband c_J is the coarse approximation of original image that contains most visual information, thresholding operation is not performed at this scale. Threshold set $T(j)$ is regulated according to the statistical properties of speckle noise as

$$T(j) = \begin{cases} 0 & j \leq N_J \\ R(j) \cdot \sigma \cdot \sigma' & j > N_J \end{cases}, \quad (11)$$

where N_J represents the levels of the approximation component c_J , $R(j)$ is the scaling factor inverse proportional to scale j , σ and σ' denote the estimation for the standard deviation of speckle noise and each curvelet coefficient.

Since the laser image has been contaminated, the standard deviation σ and σ' are not known in advance. The only method is to estimate these parameters from data I , here the classical Monte-Carlo simulation method is utilized. For the speckle noise has been transformed to

AWGN, we first generate M noise images $S_m(x, y)$ that all follow the Gaussian probability distribution function. By directly averaging these M standard images, a normalized noise image can be obtained. Then the transform coefficient set S_R of the standard noise image is obtained via a curvelet transform. Therefore, the standard deviation can be easily computed from the coefficient set. The whole procedure can be written as

$$S_R = \text{DCvT} \left(\frac{1}{M} \sum_{m=1}^M (S_m(x, y)) \right). \quad (12)$$

Curvelet is a shift variant transform, so the hard thresholding operation probably generates some visual artifacts in the despeckling image, such as the Gibbs effect and the “scratch” effect^[6]. To further improve the visual quality of despeckling image, the 2D cycle spinning in logarithmic domain is applied in the log-transformed domain. By shifting the input image with circulant shift step K_1 in horizontal and K_2 in vertical directions repeatedly, $K_1 \cdot K_2$ shifted images are generated. Then the improved hard thresholding operation is applied to each of these shifted images. Corresponding to the forward cycle spinning operation, the inverse cycle spinning and average step is applied to transform these shifted images back into a normalize image with logarithmic format. By this step, the visual artifacts can be suppressed significantly. Let Z be the shift operation, the procedure can be represented as

$$\hat{I} = \frac{1}{K_1 K_2} \sum_{i=1, j=1}^{K_1, K_2} Z_{-i, -j} \times \left(\text{DCvT}^{-1} \left(\Theta \left[\text{DCvT} \left(Z_{i, j} \left(\tilde{I} \right) \right) \right] \right) \right). \quad (13)$$

Then using a simple exponential operation to \hat{I} , the final despeckling result in the spatial domain can be obtained.

Figure 3(a) shows the laser images of an underwater triangular target captured by the ALIS at two different distances. Serious speckle noises can be found in the original laser images. The despeckling images obtained by the classical wavelet soft thresholding algorithm and the proposed curvelet based algorithm are given in Figs. 3(b) and (c), respectively. Decomposition levels and

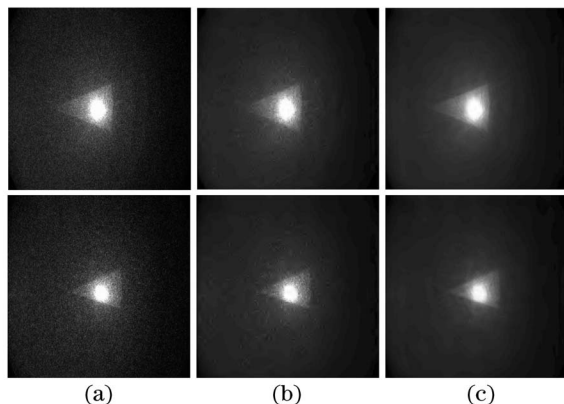


Fig. 3. Comparison of speckle reduction results for underwater laser images.

Table 1. Speckle Factor Comparison

Image	Original	Wavelet	Curvelet
	Image	Algorithm	Algorithm
1	0.2196	0.0487	0.0206
2	0.2351	0.0554	0.0219
3	0.2580	0.0593	0.0231
4	0.3064	0.0601	0.0237
5	0.3369	0.0628	0.0322

thresholds are all set to the optimal value.

It can be seen that using wavelet method, the laser images are blurred more and lots of speckle noises cannot be removed, many visual artifacts are also generated. In Fig. 3(c), the speckle noises are perfectly suppressed by the proposed algorithm, while most detail information like edges and textures are preserved.

Speckle factor Δ is adopted here as an objective criterion to evaluate the despeckling performance, which is defined as

$$\Delta = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N \frac{\sigma(i, j)}{\mu(i, j)}, \quad (14)$$

where $\sigma(i, j)$ and $\mu(i, j)$ denote the standard deviation and average of the pixel (i, j) in a filtering window of 7×7 pixels, respectively. Small value of speckle factor means good speckle reduction effect. Table 1 gives the speckle factor comparison for five laser underwater images of different distances. We can see that the proposed algorithm can always obtain better speckle suppression performance.

In this letter, a curvelet based speckle reduction algorithm for underwater laser image is presented. The main idea is to suppress speckle noise in curvelet domain, other techniques including logarithmic transform, improved hard thresholding, cycle spinning, and Monte-Carlo simulation are also utilized. Experimental results prove the validity of the proposed algorithm.

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