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Image Despeckling Based on LMMSE Wavelet Shrinkage

***Abstract**. A low complexity method for suppressing speckle in synthetic aperture radar (SAR) images is proposed. This method doesn't require the logarithmic transform and is an extension of the linear minimum mean square error (LMMSE) filter to the image wavelet representation. A spatially adaptive shrinkage function is obtained and each modified coefficient is decided separately. Simulation results for the simulated SAR images demonstrate the proposed method outperforms some representative SAR despeckling methods.*

***Streszczenie.** Zaproponowano metodę poprawy jakości obrazu w radarach typu SAR. Bazuje ona na liniowym minimum średniej kwadratu błędu LMMSE filtru. Wykorzystano adaptacyjną funkcję zbieżną w przestrzeni i wszystkie współczynniki modyfikowane są niezależnie. (**Poprawa jakości obrazu przy wykorzystaniu falkowej zbieżności LMMSE**)*

Keywords: synthetic aperture radar (SAR); speckle; wavelet transform; linear minimum mean square error (LMMSE).
Słowa kluczowe: radar typu SAR, jakość obrazu/.

Introduction

Synthetic aperture radar (SAR) images provide useful information for many applications, such as reconnaissance, surveillance, and targeting. However, the automatic interpretation of SAR images is often extremely difficult due to speckle noise. Thus, despeckling has become an important issue in SAR image processing.

Many algorithms have been developed to suppress speckle noise. Usually, the speckle is partially suppressed already during the image formation process by multilook processing. But multilook averaging reduces the standard deviation of speckle but it also deteriorates the spatial resolution. Another traditional approach is spatial filtering, including the Lee filter, the Frost filter, the Gamma MAP filter and their variations such as the enhanced Lee filter. The performance of these filters depends heavily on the choice of the local window, and exhibit limitations in preserving the detail in weakly textured areas.

To overcome these disadvantages, wavelet-based algorithms [1, 2] have been widely used to reduce speckle noise. Wavelet theory provides a powerful tool for detecting image feature at different scales. Due to this property, the despeckling approaches based on wavelet transform can well preserve details of the original image. Speckle in SAR images is multiplicative, whereas most existing wavelet denoising algorithms are developed for additive noise. To take advantage of the available algorithms based on wavelet transform, the log-transform is applied to SAR image to convert the multiplicative noise to additive noise before performing wavelet denoising [3, 4]. After wavelet denoising on log-transformed image, an exponential operation is employed to convert the image back to a non-logarithmic format. The major disadvantage of such approaches is that the backscatter mean is not preserved in homogeneous areas when the image is converted back to a non-logarithmic format after denoising. Furthermore, signal variations are damped by the logarithm, resulting in an unlikely "flatness" after despeckling.

To eliminate the impact of log-transform to denoising performance, some algorithms without performing the logarithmic transform have been proposed. Xie et al. propose a low-complexity wavelet denoising process based on the minimum mean square error (MMSE) estimation [5]. But the discrete wavelet transform (DWT) is applied during image denoising. The DWT is critically sub-sampled and time variant, which affects the performance of the despeckling. Alternative approaches have been proposed that are based on the stationary wavelet transform (SWT), which is a time-invariant transform. Foucher et al. propose a SWT despeckling algorithm using the maximum a posteriori (MAP) criterion [6], in which the Pearson distribution is used to model the probability density function (pdf) of wavelet coefficients. Although this algorithm has good performance, the high computational complexity of the Pearson distribution makes this approach rarely used in practice. To simplify calculations, Argenti et al. introduce a local linear MMSE (LMMSE) filter [7] in the undecimated wavelet domain. Dai et al. present a despeckling method based on the mixture-Gaussian distribution model of SWT wavelet coefficients [8].

In this paper, a low complexity SWT despeckling method is proposed, which is an extension of the LMMSE filter to the image wavelet representation.

Speckle model

Speckle noise in SAR images arises as a consequence of the coherent illumination used by radar. Within each ground resolution cell a large number of elementary reflectors reflects the radar wave towards the sensor. For a surface that is rough on the scale of the radar wavelength, the number of elementary reflectors is large enough to ensure the statistical independence in phase and amplitude of the elementary backscattered waves. For this type of areas, the speckle is fully developed. In this paper, the speckle is assumed to be fully developed, which is valid for homogeneous targets and weakly textured areas, but is only an approximation for point targets and extremely heterogeneous areas.

For a SAR image in which the speckle is fully developed, a multiplicative noise model is often employed, which can be expressed as

(1) $$v = fz$$

Where v is the observed noisy signal, f is the noise-free signal and z is the normalized speckle random variable independent of f with unit mean, respectively. The intensity image is considered in this paper, which is usually used one of SAR images formats. In the intensity format, z follows the Gamma distribution. The multiplicative noise model in (1) can easily be decomposed into an additive model in the following form

(2) $$v = fz = f + f(z-1) = f + fz' = f + b$$

where z' is a random variable independent of f with zero mean, and b is the additive noise depending on the underlying unknown signal f.

LMMSE despeckling in the stationary wavelet domain

In signal processing, the representation of signal plays a fundamental role. Wavelet transform is a powerful tool to facilitate the representation and analysis of transient signals.

For the SAR image despeckling, DWT is often used. But DWT is not invariant under translation. The lack of shift invariance limits the performance of DWT in despeckling. In order to preserve the translation invariance property, the stationary wavelet transform is introduced in despeckling. A stationary wavelet transform requires more calculations and calls for bigger memory. However, it enables a better despeckling quality. A common despeckling procedure with wavelets is: 1) Compute the wavelet transform; 2) Remove speckle noise from the wavelet coefficients and 3) Reconstruct the despeckled image. The scaling coefficients are usually kept unchanged. During this procedure, the second step is the most important. In this paper, LMMSE technique is used to estimate the desired noise-free wavelet coefficient in the second step.

Due to linearity of the wavelet transform, the additive model (2) remains additive in the transform domain as well

(3) $$w = y + n,$$

where w is the observed wavelet coefficient, y is the noise-free coefficient, n is the additive noise. The LMMSE estimate of y is derived as

(4) $$\hat{y} = \eta w,$$

where

(5) $$\eta = \frac{E\left[w^2\right] - E[wn]}{E\left[w^2\right]}.$$

According to (4) and (5), it is necessary to estimate $E\left[w^2\right]$ and $E[wn]$ to calculate $\hat{y}$. In this paper, a local adaptive algorithm is proposed to estimate $E\left[w^2\right]$ and $E[wn]$.

Replacing w with $y+n$ according to equation (3), it can be obtained

(6) $$E[wn] = E[yn] + E\left[n^2\right].$$

The stationary wavelet transform is computed with the à Trous algorithm. According to this algorithm, the wavelet coefficient $y_j^{\mathrm{HL}}(a,b)$ at resolution scale 2^j, spatial position (a , b) , and HL subband corresponding to horizontal direction can be expressed as

(7) $$y_j^{\mathrm{HL}}(a,b) = \sum_{l,k} h_j^{eq}(l) g_j^{eq}(k) f(a+l, b+k),$$

where $h_j^{eq}(l)$ and $g_j^{eq}(k)$ are the coefficients of the equivalent filters at the scale 2^j. And that

(8) $$h_j^{eq}(l) = h_{j-1}(m_j) h_{j-2}(m_{j-1}) \cdots h_0(m_1),$$

(9) $$g_j^{eq}(k) = g_{j-1}(n_j) h_{j-2}(n_{j-1}) \cdots h_0(n_1),$$

where $l = m_1 + m_2 + \cdots + m_j$, $k = n_1 + n_2 + \cdots + n_j$, $h_{j-1}(m_j)$ is the coefficient of the lowpass filter at the scale 2^j, and $g_{j-1}(n_j)$ is the coefficient of the highpass filter at the scale 2^j. Similarly,

(10) $$y_j^{\mathrm{LH}}(a,b) = \sum_{l,k} g_j^{eq}(k) h_j^{eq}(l) f(a+k, b+l),$$

(11) $$y_j^{\mathrm{HH}}(a,b) = \sum_{l,k} g_j^{eq}(l) g_j^{eq}(k) f(a+l, b+k),$$

where

(12) $$g_j^{eq}(l) = g_{j-1}(m_j) h_{j-2}(m_{j-1}) \cdots h_0(m_1),$$

LH and HH stand for the orientation subbands corresponding to the vertical and diagonal directions respectively. Similarly,

(13) $$n_j^{\mathrm{HL}}(a,b) = \sum_{l,k} h_j^{eq}(l) g_j^{eq}(k) f(a+l, b+k) z'(a+l, b+k),$$

(14) $$n_j^{\mathrm{LH}}(a,b) = \sum_{l,k} g_j^{eq}(k) h_j^{eq}(l) f(a+k, b+l) z'(a+k, b+l),$$

(15) $$n_j^{\mathrm{HH}}(a,b) = \sum_{l,k} g_j^{eq}(l) g_j^{eq}(k) f(a+l, b+k) z'(a+l, b+k).$$

Since z' is a random variable independent of f with zero mean, it can be derived

(16) $$E\left[Y_j^{HL}(a,b) N_j^{HL}(a,b)\right] = E\left[\sum_{l,k} h_j^{eq}(l) g_j^{eq}(k) F(a+l,b+k) \cdot \sum_{l,k} h_j^{eq}(l) g_j^{eq}(k) F(a+l,b+k) Z'(a+l,b+k)\right] = 0.$$

If it is assumed that z is independent and equally distributed, $E\left[n_j^{\mathrm{HL}}(a,b)^2\right]$ is calculated by

(17) $$\begin{aligned} &E\left[n_j^{\mathrm{HL}}(a,b)^2\right] \\ &= E\left[\left(\sum_{l,k} h_j^{eq}(l) g_j^{eq}(k) b(a+l, b+k)\right)^2\right] \\ &= \sum_{l',k'} \sum_{l,k} \left[h_j^{eq}(l') h_j^{eq}(l) g_j^{eq}(k') g_j^{eq}(k) \right. \\ &\quad \cdot f(a+l', b+k') f(a+l, b+k) \\ &\quad \left. \cdot z'(a+l', b+k') z'(a+l, b+k)\right] \\ &= \sigma_z^2 \sum_{l,k} h_j^{eq}(l)^2 g_j^{eq}(k)^2 E\left[f(a+l, b+k)^2\right] \\ &\quad + \sum_{l',k'} \sum_{l \neq l', k \neq k'} \left\{h_j^{eq}(l') h_j^{eq}(l) g_j^{eq}(k') g_j^{eq}(k) \right. \\ &\quad \cdot E\left[f(a+l', b+k') f(a+l, b+k)\right] \\ &\quad \left. \cdot E\left[z'(a+l', b+k') z'(a+l, b+k)\right]\right\} \\ &= \sigma_z^2 \sum_{l,k} h_j^{eq}(l)^2 g_j^{eq}(k)^2 E\left[f(a+l, b+k)^2\right] \end{aligned},$$

where σ_z^2 is the variance of z. If the variance of f is assumed to be zero within the support region of the equivalent filters, $E\left[n_j^{\mathrm{HL}}(a,b)^2\right]$ can be further estimated by

(18) $$E\left[n_j^{\mathrm{HL}}(a,b)^2\right] = \sigma_Z^2 \sum_{l,k} h_j^{eq}(l)^2 g_j^{eq}(k)^2 \left\{E\left[f(a+l, b+k)\right]\right\}^2.$$

Furthermore due to $E[v] = E[f]$, it turns out that

(19) $$E\left[n_j^{\mathrm{HL}}(a,b)^2\right] = \sigma_Z^2 \sum_{l,k} h_j^{eq}(l)^2 g_j^{eq}(k)^2 \left\{E\left[v(a+l, b+k)\right]\right\}^2.$$

Therefore,

(20) $$E\left[w_j^{\mathrm{HL}}(a,b)n_j^{\mathrm{HL}}(a,b)\right] = \sigma_Z^2 \sum_{l,k} h_j^{eq}(l)^2 g_j^{eq}(k)^2 \left\{E\left[v(a+l,b+k)\right]\right\}^2 .$$

Similarly,

(21) $$E\left[w_j^{\mathrm{LH}}(a,b)n_j^{\mathrm{LH}}(a,b)\right] = \sigma_z^2 \sum_{l,k} g_j^{eq}(k)^2 h_j^{eq}(l)^2 \left\{E\left[v(a+k,b+l)\right]\right\}^2 ,$$

(22) $$E\left[w_j^{\mathrm{HH}}(a,b)n_j^{\mathrm{HH}}(a,b)\right] = \sigma_z^2 \sum_{l,k} g_j^{eq}(l)^2 g_j^{eq}(k)^2 \left\{E\left[v(a+l,b+k)\right]\right\}^2 .$$

where $\sigma_z^2 = 1/L$ in *L*-look image . If the observed noisy signals are assumed to be identically distributed within the neighborhood system of pixel (a,b), its mean at pixel (a,b) can be estimated by

(23) $$E\left[v(a,b)\right] = \frac{1}{K \times K} \sum_{(l,k)\in\kappa(a,b)} v(l,k) ,$$

where $\kappa(a,b)$ denotes the neighborhood system of pixel (a,b) and $K \times K$ is corresponding dimension. In the similar way, the second-order moment of the wavelet coefficient w at pixel (a,b) is estimated using neighboring coefficients in the following form by assumed that theirs distribution is identical in the neighborhood system of pixel (a,b)

(24) $$E\left[w(a,b)^2\right] = \frac{1}{M \times M} \sum_{(l,k)\in\nu(a,b)} w(l,k)^2 ,$$

where $\nu(a,b)$ denotes the neighborhood system of pixel (a,b) and $M \times M$ is corresponding dimension.

Once $E[wn]$ and $E[w^2]$ are calculated according to (20), (21), (22) and (24), y can be estimated in (4).

Experimental results

The performance of the proposed despecking algorithm for simulated SAR images will be illustrated with a quantitative and a qualitative performance measure. The qualitative measure is the visual quality of the resulting image. The signal-to-noise (SNR) is used as the quantitative measure.

The performance will be illustrated on the 256×256 simulated SAR images with artificial noise. Two test images are Lena and House respectively, which are corrupted by the simulated speckle. The variation on the CDF-(spline)-filters "with less dissimilar lengths" is used to implement the stationary wavelet transform. Primal and dual wavelets have four vanishing moments. These wavelets are rather popular in image processing. With this transform, the input image is decomposed over three levels. For comparison, the improvements in terms of SNR of the proposed methods and the five related methods are summarized in Table 1, Table 2 respectively. All despeckling methods obviously achieve a higher gain in SNR when the input image is noisier, but the proposed method performs better than the other related methods.

However, it is not sufficient to rely on quantitative measures only, since they cannot take into account all aspects of image quality for which the human eye is sensitive. Fig.1 presents the original Lena image and the same image with artificial speckle noise (L=24). The result of the proposed despecking method and the other related methods are shown in Fig.2. The proposed method achieves the most successful noise reduction in homogeneous areas.

Table 1. Comparison of quantitative result for Lena image in SNR (dB)

Looks	1	2	6	12	24	36
Noise	-6.66	-3.51	1.15	4.30	7.21	8.99
This Study	6.60	8.53	11.63	13.54	15.47	16.54
GMMMSE[8]	5.49	6.74	9.45	11.61	13.74	15.06
LLMMSE[7]	5.90	8.07	11.14	13.26	15.18	16.53
GMMRF[3]	5.73	7.88	10.69	12.55	14.42	15.74
BayesShrink[4]	6.28	7.58	9.95	11.55	13.09	14.22
Kuan[9]	5.53	6.87	9.46	11.33	13.05	14.29

Table 2. Comparison of quantitative result for House image in SNR (dB)

Looks	1	2	6	12	24	36
Noise	-8.14	-5.17	-0.37	2.66	5.67	7.44
This Study	6.98	8.28	11.74	13.87	15.90	17.16
GMMMSE[8]	5.49	6.74	9.45	11.61	13.74	15.06
LLMMSE[7]	5.42	7.64	11.08	13.22	15.31	16.40
GMMRF[3]	5.62	7.77	11.14	12.90	14.54	15.63
BayesShrink[4]	6.60	8.13	10.71	11.98	13.53	14.52
Kuan[9]	4.59	6.27	8.81	10.62	12.36	13.52

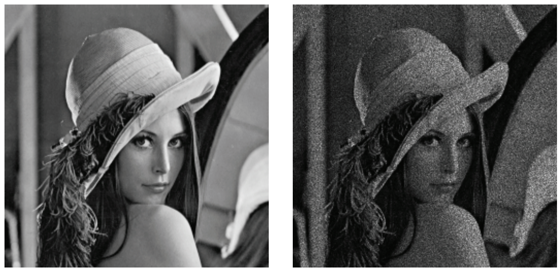

Fig.1. Original Lena image (left) and the same image with artificial speckle noise (L=24, right).

(a) The proposed method (b) GMMMSE

(c) LLMMSE (d) GMMRF

(e) BayesShrink (f) Kuan

Fig.2. Comparison of dfferent despeckling methods for noisy Lena image of Fig.1

Conclusion

To improve the despeckling performance, a low complexity despeckling method based on LMMSE wavelet shrinkage is proposed in this paper. This method is an extension of LMMSE filter to the image wavelet representation. Based on the time-frequency analysis property of stationary wavelet transform, the parameter of LMMSE wavelet shrinkage is estimated. Experiment results demonstrate this method improves the despeckling performance quantitatively and qualitatively in homogeneous areas.

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