ADAPTIVE DESPECKLING SAR IMAGES BASED ON SCALE SPACE CORRELATION

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ABSTRACT

A new adaptive filtering algorithm is proposed to remove speckle in SAR images in this paper. This method differentiates the edge information of detail from the noisy images based on scale space correlation. The Wiener filter is used to deal with the edge information of points and the Bayesian soft threshold is applied on the noisy points in homogeneous areas to reduce speckle. After processed with this algorithm, SAR images can not only achieve satisfied despeckling effect but also show a good performance of preserving details and texture information.

1. INTRODUCTION

SAR images suffer from a special kind of noise called 'speckle'. Speckle can significantly degrade the image quality and hence increases great difficulty for the observer to extract fine detail and textural information from SAR images. Therefore how to restore SAR image from speckle has become a necessary step in post-processing of imaging. In a common sense, speckle is formed due to the coherent accumulation of many random distributing scatters' echoes in the same resolution cell. The majority of despeckling filters rely on the multiplicative speckle model, which combines the watched signal with the reflecting modulus of ground surface and the noise modulus in a theoretical sense. When the coarse level of ground surface and the wavelength of radar are comparable, we suppose the multiplicative model is proper and the speckle to be fully developed. However, this is generally not true for built-up areas, such as the edges and textural areas comprising a lot of fine details. Some conventional algorithms blur the edges due to ignoring this point and lose much useful information as a result, which severely degrades the despeckling quality. So a good adaptive speckle filter should possess two fundamental properties: 1.effective speckle reduction in statistically homogeneous areas; 2. good feature preservation in edges and real textual variations.

Up to now, there are a lot of approaches to suppress speckle, traditionally including two types of methods. The first one is the simplest approach, referred to multilook despeckling[1], which involves averaging the intensity over several pixels corresponding to multilook. Although this approach can effectively suppress speckle, meanwhile it also severely reduces the spatial resolution of SAR images. The other type of approach is adaptive spatial filtering through analysis of the local statistical property surrounding a given pixels, such as the filters proposed by Lee[2] and its variations, the refined Lee filter[3] . But these approaches are usually difficult for us to select a proper window size according to the image's local statistics. In this decade, multiresolution analysis has become the focus of image processing because it has the very useful property of space and scale localization. However most of the thresholds proposed have no way to accurately match with the different distribution of signal and noise power in various scale and orientation, which can lead to loss of much detail information during despeckling. In order to solve this problem, many scholars proposed various kinds of adaptive filtering algorithms using multiresolution techniques, such as the wiener filtering in wavelet domain[4] and the spatially adaptive wavelet threshold[5]. Although these approaches show a superior performance of preserving details but are poor in removing speckle, especially for SAR images, which usually have more severe speckles than other common images.

According to this, a new adaptive filtering algorithm based on the scale space correlation[6] is proposed in this paper, which differentiates the edges and textural information from each subband by the means of scale correlation and respectively deals the detail and noisy points with the Wiener filters possessing good property of preserving details and the Bayesian soft threshold to efficiently remove speckles. In this way we can acquire better despeckling effect in speckle reduction and feature preservation. Furthermore our algorithm can be easily implemented and has a lower computation burden than other pixel by pixel adaptive filtering techniques so it possesses widely applicability.

2. SCALE SPACE CORRELATION

The scale space correlation[6] relies on the variations in scale of the wavelet transform data of the signal because the sharp edges have large modulus over many wavelet scales while the magnitudes of the wavelet coefficients representing pure noise rapidly diminish as the scale increases. Therefore we can detect major edges in every scale of an image by means of direct multiplication of wavelet transform data at adjacent scales.

Firstly we convert the original multiplicative speckle in SAR images into additive noise with logarithm transform. Due to the shift-invariance property of stationary wavelet transform(SWT) and its constant signal length after every wavelet decomposition, we use the discrete SWT to decompose image into multi-scales in this paper.

Let $F(x,y)$ be the 2-D signal ready to be decomposed. Then the two-dimensional wavelet transform is represented in (1) and (2).

$$F(x,y)=\sum_m\sum_x\sum_y \psi'_{m,x,y}(x,y)W(m,x,y) \tag{1}$$

$$W(m,x,y)=\int_{-\infty}^{+\infty}dx\int_{-\infty}^{+\infty}dy\times\overline{\psi_{m,x,y}(x,y)}F(x,y) \tag{2}$$

Where $\psi_{m,x,y}(x,y)$ is the 2-D wavelet kernel and $\psi'_{m,x,y}$ is the dual basis of $\psi_{m,x,y}$. The scale index m is not greater than $M=\log_2[\min(x_{\max},y_{\max})]$. $x_{\max}$ and $y_{\max}$ are separately the maximum length of the image's two dimension. $W(m,x,y)$ is the transformed image data. Then the scale space correlation function can be defined as:

$$Corr_l(m,x,y)=\prod_{i=0}^{l-1}W(m+i,x,y)$$
$$1\le x\le x_{\max},1\le y\le y_{\max} \tag{3}$$

Where l is the number of resolution scales involved in the direct multiplication, which is usually 2 or 3. Here we suppose $l=2$. m is the current processed scale.

For each detail image of every scale we associate a mask $p_{m,x,y}$ of binary labels with every wavelet coefficient $W(m,x,y)$ to classify different pixels. The pixels labeled with $p_{m,x,y}=1$ represent the modulus of signal while others represent the noisy modulus. The whole process is shown as follows:

1. Initialize the mask $p_{m,x,y}$ with zero; Use the 2-D stationary wavelet transform to decompose the image into N scales($m=1,2\ldots N$).
2. In the intended detail of the m scale, we make the adjacent scale correlation according to (3) and compute the power of $Corr_2(m)$ and $W(m)$:

$$PCorr(m)=\sum_x\sum_y Corr_2(m,x,y)^2$$
$$PW(m)=\sum_x\sum_y W(m,x,y)^2 \tag{4}$$

Then rescale $Corr_2(m,x,y)$ to $W(m,x,y)$ at every pixel:

$$Corr_2(m,x,y)=Corr_2(m,x,y)*\sqrt{\frac{PW(m)}{PCorr(m)}} \tag{5}$$

3. Compare every updating values of $|Corr_2(m,x,y)|$ and $|W(m,x,y)|$.
If $|Corr_2(m,x,y)|>|W(m,x,y)|$,
$p_{m,x,y}=1$, $Corr_2(m,x,y)=0$, $W(m,x,y)=0$.
Calculate $p_{m,x,y}$ of all points in the intended detail and update the corresponding $Corr_2(m,x,y)$ and $W(m,x,y)$.
4. Repeat 2 to 3 until the power of all the wavelet coefficients in the detail $PW(m)\le$ noise power and then save the p_m.
5. Estimate all the p_m in other detail images.

3. ADAPTIVE FILTERING PROCESS

Let $g=f\cdot u$ represent the 2-D image contaminated by speckle, where f implies the original clean image, u represents the multiplicative Gaussian noise, whose mean value is 1 and which is relatively independent with the signal f. After apply the logarithm transform to $g=f\cdot u$, we can get:

$$\log g(x,y)=\log f(x,y)+\log u(x,y)\quad (x,y)\in Z^2 \tag{6}$$

Implement the 2-D stationary wavelet transform to $\log g(x,y)$, (6) can be rewritten into:

$$W(x,y)=S(x,y)+Z(x,y) \tag{7}$$

Where W, S and Z are respectively referred to the wavelet coefficients of $\log g$, $\log f$ and $\log u$.

Suppose $W(x,y)$ is the wavelet coefficients and $S(x,y)$ is the filtered result. $S(x,y)$ can be calculated from the following formula according to Wiener filter:

$$S(x,y)=m_s(x,y)+\frac{\sigma_s^2(x,y)}{\sigma_s^2(x,y)+\sigma_z^2}\times(W(x,y)-m_s(x,y)) \tag{8}$$

Where $m_s(x,y)$ is the mean of all the points in the local window centered with the intended point and here we suppose the window size is $K\times L$, so:

$$m_s(x,y)=\frac{1}{KL}\sum_{n_1=1}^{K}\sum_{n_2=1}^{L}W(n_1,n_2) \tag{9}$$

$$\sigma^2(x,y)=\frac{1}{KL}\sum_{n_1=1}^{K}\sum_{n_2=1}^{L}(W(n_1,n_2)-m_s(x,y))^2 \tag{10}$$

In (10), $\sigma^2(x,y)$ is the variance of all the points in the local window and

$$\sigma^2(x,y)=\sigma_s^2(x,y)+\sigma_z^2 \tag{11}$$

Where $\sigma_s^2(x,y)$ and σ_z^2 are separately the variance of the signal and noise. Hence from (11) we can deduce $\sigma_s^2(x,y)=\sigma^2(x,y)-\sigma_z^2$. For every pixel labeled as $p_{m,x,y}=1$, we should update the value according to (8).

Meanwhile we use the Bayesian soft threshold to denoise the pixels whose $p_{m,x,y}$ is labeled as 0. The threshold T has an approximate solution in the following form[7]:

$T(\sigma_S) \propto \sigma_Z^2 / \sigma_S$, which means the larger the signal's variance, the smaller the threshold and the better the despeckling effect. This paper uses a modified threshold of $T(\sigma_S)$:

$$T = K\frac{\sigma_Z^2}{\sigma_S} \tag{12}$$

Where $K = \sqrt{\log \gamma(L)}$ is an adjusting modulus that is proportional to the length of the image. γ is a constant to automatically adjust the denoising threshold according to the property of the processed image. We estimate the noise variance in the way that $\hat{\sigma}_Z^2 = \left[\frac{median\left|W_{x,y}\right|}{0.6745}\right]^2$, where $W_{x,y} \in HH_1$, defined as the coefficients of the diagonal detail in the first scale. From the result of $\hat{\sigma}_Z^2$ we can compute $\hat{\sigma}_S$ in the following way:

$$\hat{\sigma}_S = \sqrt{\max(\hat{\sigma}_W^2 - \hat{\sigma}_Z^2, 0)} \tag{13}$$

From (13) we can avoid the possibility that $\hat{\sigma}_S$ becomes negative resulted from $\hat{\sigma}_W^2 < \hat{\sigma}_Z^2$ due to limited sampling numbers. Since the mean of $W_{x,y}$ is close to zero, we can compute its variance in (14):

$$\hat{\sigma}_W = \sqrt{\frac{1}{L^2}\sum_{x,y=1}^{L} W_{x,y}^2} \tag{14}$$

4. THE ALGORITHM REVIEW

This section gives the whole process of the algorithm. It's description is as follows:

1. Apply the logarithm transform to the original SAR image and decompose it into several scale resolutions through 2-D stationary wavelet transform.
2. Estimate the noise variance from the diagonal detail of the first scale (HH).
3. In every detail image we estimate the associated binary masks in the way introduced in the second section.
4. Compute the Bayesian soft threshold in every detail image of different scales.

a. Evaluate the standard deviation σ_s of the intended image according to (13).

b. If $\sigma_s > 0$, we use (12) to get the denoising threshold; Otherwise if $\sigma_s = 0$, select the maximum value of the detail image's wavelet coefficients as the threshold.

5. Use the wiener filter to deal with the pixels labeled by mask 1; Use the Bayesian soft threshold to deal with the pixels labeled by 0.
6. Reconstruct the SAR image by the inverse stationary wavelet transform.

7 Make the exponential transform to the result of step 6.

In the process, we usually decompose the image into 6 scale resolutions with the stationary wavelet transform to acquire a better precision.

From the statistical viewpoint, wiener filter has a more complex computation process than normal threshold methods because it is associated with the calculation of every pixel's mean and variance except some other fundamental computation. As we classify the pixels before despeckling processing and treat most of them with threshold method instead of wiener filter, we can reduce the computation time to implement the whole program, in contrast with the normal pixel to pixel adaptive filtering techniques, such as wiener filter. In practical experiments, wiener filter will probably suffer from shortage of memory if the image is too large while our algorithm seems to be more superior at saving physical computer resource with the increase of image's size. Additionally our algorithm is a real adaptive filtering process because it treats the pixels of the image with different ways according to their statistics, both corresponding to various scales and also to every single point.

5. RESULTS AND COMPARISONS

In this section, we evaluate the performance of our proposed adaptive despeckling algorithm with real SAR images and compare it with other conventional filtering approaches. Fig.1 is a SAR image of 256×256 size. This experiment decomposes the image transformed with logarithm into 6 scale resolutions and the base function of wavelet transform is Daubechies4. In(12), $K = \sqrt{\log 10(L)}$, according to the practical situation of processed images. We use the local equivalent number of looks (ENL)[1] to measure the noise reduction level. It is better at noise reduction if the ENL is higher. The equivalent number of looks can be defined in the way: $ENL = \left(\mu/\sigma\right)^2$, where μ is the mean of the points in the homogeneous areas of the recovered image and σ is the standard deviation.

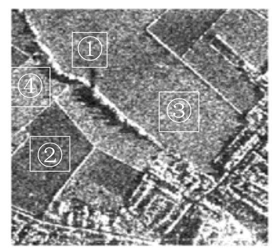
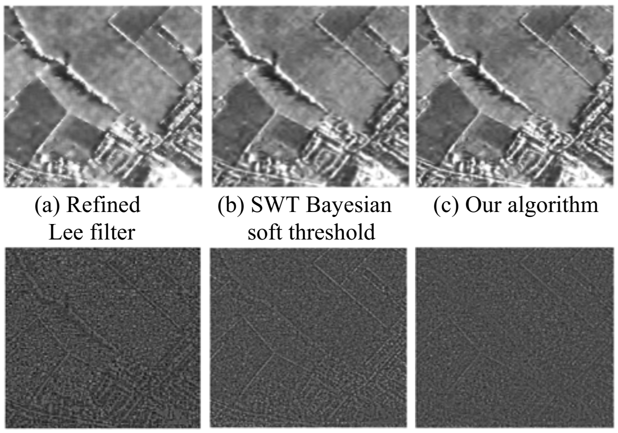


Fig.1 Original image

In this experiment, four different local areas labeled in the SAR image(Fig.1) are selected to evaluate the performance of the proposed despeckling algorithm and their ENL are listed in the TABLE 1. Meanwhile since the speckle is based on a multiplicative model, we can approximately regard the ratio image acquired from the original noisy image divided by the recovered image as the noise image[Fig.2 (d),(e),(f)], through which we can directly observe the despeckling effect and detail preservation of our algorithm.



(a) Refined Lee filter; (b) SWT Bayesian soft threshold; (c) Our algorithm

(d) Ratio image of (a); (e) Ratio image of (b); (f) Ratio image of (c)

Fig.2 Experiment results

From the results, we can see that Refined Lee filter[3] loses much useful detail information although it despeckles the noisy image more smoothly, especially for the right lower corner in the Fig.2(a), seeming to be more blur than before recovered. In contrast with it, the SWT Bayesian soft threshold [Fig.2(b)] has a better effect of preserving details but still cannot acquire satisfied despeckling results. Under the consideration of all aspects, our paper proposes a new adaptive algorithm based on the scale space correlation to deal two types of pixels with different filtering techniques. From the result images, in Fig.2(c) and Fig.2(f), we can conclude that our approach obtains nearly the same despeckling effect in homogeneous areas as the SWT Bayesian soft threshold and seems to be more superior at feature preservation than the latter one. This conclusion is also reasonable in a theoretic sense. Therefore from the results of experiments we can see that our algorithm has a superior performance than other conventional approaches from the overall property.

Table 1. ENL of Fig.1 and its recovered result

Areas / Algorithm	Area ①	Area ②	Area ③	Area ④
Original SAR Image	10.04	8.61	12.57	11.43
Refined Lee Filter	96.47	80.63	204.23	207.55
SWT Bayesian Soft Threshold	95.68	82.93	278.01	180.43
Our algorithm	96.12	78.65	266.64	139.01

6.CONCLUSIONS

We have proposed a new adaptive filtering algorithm to despeckle SAR images based on the scale space correlation. In order to convert the multiplicative speckle model into an additive noise we apply the logarithmic transform to SAR images and decompose the noisy image into multi-scales by the means of 2-D stationary wavelet transform. In every detail image the adjacent scale correlation is used to classify the pixels into two different groups: detail information and noise coefficients. According to the two kinds of pixels' statistical property, this proposed algorithm incorporates the Wiener filter and Bayesian soft threshold to separately deal with these pixels one by one. Experimental results indicate that this new algorithm has better satisfied performance in terms of speckle reduction and detail preservation than other conventional approaches. Furthermore, it can be easily implemented and has a lower computation burden than other adaptive filtering algorithm. Therefore it has a widely applicability in practice.

7. REFERENCES

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