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A Modified Bilateral Filter for SAR Image Speckle Reduction

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Abstract. Bilateral filter can not only smooth images, but also preserve edges. The filtering result is always influenced by the variance of spatial closeness and that of gray value similarity. It is difficult to configure two parameters to the optimum. In this paper, the parameter estimation method proposed in [11] was improved, and a modified bilateral filter was presented. De-speckling experiments on real SAR image and their quantitative measure demonstrate new method is superior to that in [11] on smoothing images and preserving edges.

Keywords: synthetic aperture radar, bilateral filter, speckles reduction.

1. Introduction

The speckle noise exists in the Synthetic aperture radar (SAR) images because of the SAR coherent imaging mechanics. The speckle noise seriously affects the further applications of SAR images.

The local adaptive filtering is an important class of filtering to de-speckling, such as: Lee filtering [1], Kuan filtering [2], Frost filtering [3] and Sigma filtering [4] etc. These algorithms are mainly suitable for homogeneous regions in SAR images. In order to meet the non-homogeneous regions, based on the classical algorithms, the improved or enhancement algorithms were proposed, such as: refined Lee filtering [5], weighting filtering [6], hybrid sigma filtering [7] and improved sigma filtering [8] etc. Lopes [9] presented enhancement Lee filtering, enhancement Kuan filtering and enhancement Frost filtering. These filtering algorithms can smooth the images, though to some extent to keep the image details, but the image contrast is still reduced, that is, the edges are blurred.

Tomasi and Manduchi [10] proposed a bilateral filtering (BF). Because the filtering algorithm takes into account the geometric closeness and gray value similarity simultaneously, it can effectively smooth the images, while preserving edges. The BF was extended to the SAR images de-speckling by Zhang [11]. Zhang proposed a method to estimate the variance of spatial closeness (σ_d) and that of gray value similarity (σ_r).

De-speckling estimation indexes include the equivalent number of looks (ENL) [12] and edge preserving index (EPI) [13]. The greater the ENL, the stronger the ability of filtering algorithm smoothing images. The greater the EPI, the better the ability of filtering algorithm preserving edges information. We analyzed the variation of normalized ENL and normalized EPI with σ_d and σ_r based on the idea in [14], improved the parameters estimation method in [11], and presented a modified bilateral filtering (MBF). De-speckling experiments on real SAR image and their quantitative measure demonstrate MBF is superior to BF on smoothing images and preserving edges.

2. Bilateral Filtering

The bilateral filter proposed by Tomasi and Manduchi [10] is the combination of spatial filter and range filter. It can be described as follows:

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$$h(x)=k^{-1}(x)\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}f(\xi)c(\xi,x)s(f(\xi),f(x))d\xi \tag{1}$$

$$k(x)=\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}c(\xi,x)s(f(\xi),f(x))d\xi \tag{2}$$

Where $f(*)$ is input image, $h(*)$ is output image, x is current pixel, ξ is the pixel in the neighbourhood of x. $c(\xi,x)$ measures the geometric closeness between x and ξ, and $s(f(\xi),f(x))$ measures the gray value similarity between x and ξ. For shift-invariant Gaussian filtering, they can be described as follows:

$$c(\xi,x)=\exp(-1/2(\|\xi-x\|/\sigma_d)^2) \tag{3}$$

$$s(\xi,x)=\exp(-1/2(\|f(\xi)-f(x)\|/\sigma_r)^2) \tag{4}$$

The key problem of bilateral filtering is to configure the parameters σ_d and σ_r.

An estimation method on the parameters was proposed in [11]. The paper showed that σ_r was more sensitive to ENL than σ_d. The author fixed σ_d first, filtered the image using BF with the parameters σ_d and σ_{ri} (i=1,2,…, n), ENL and EPI was calculated for the every filtering result, respectively. If the following condition (5) was satisfied, the σ_{ri} was regarded as the best σ_r, denoted as σ_{r_best}.

$$\text{ENL(i-1)} < \text{EPI(i-1)}\ \&\&\ \text{ENL(i+1)} > \text{EPI(i+1)} \tag{5}$$

The estimation of σ_{d_best} is similar to that of σ_{r_best}. Finally the bilateral filtering with the (σ_{r_best}, σ_{d_best}) and post-processing were applied to the images. More details can refer to [11]. Estimating the σ_r and σ_d, the variation tendency of EPI with (σ_d, σ_r) and the number of σ_{ri} satisfying (5) are not taken into account. In this paper, we improve the estimation method of σ_d and σ_r, and get better σ_{r_best} and σ_{d_best}.

3. Modified Bilateral Filfer

Fig.1 is an airborne SAR image of Sports Complex at Stadium & University, Albuquerque, New Mexico, America (1-m resolution). We analyze the homogenous region I and II.

Fig.2 illustrates the variation of normalized ENL and normalized EPI with σ_r when σ_d =3 using the BF in [11] based on the idea in [14] about region II, and we get the σ_{r_best} =0.15. In fact, there are two σ_r satisfying the (5), 0.15 and 0.20, respectively. From the Fig.2, 0.20 is closer to the intersection point than 0.15, so the σ_{r_best} is not most suitable.

Fig.3 illustrates the variation tendency of normalized ENL and normalized EPI with σ_d about different σ_r. From Fig.3, we find that ENL increases with σ_d increasing, EPI first decreases, and then increases with σ_d increasing, and the rate of increase gradually slows. Fig.3 demonstrates when σ_r fixed, as far as σ_d is concerned, the bigger the better. Considering the amount of calculation and variation tendency, we configure the $\sigma_d = \lfloor 0.75\times N \rfloor$, where N is size of bilateral filtering half-width, $\lfloor * \rfloor$ is rounded down. Now, the key is to get the σ_{r_best}.

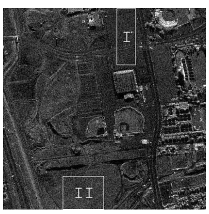


Fig. 1: An airborne SAR image of Sports Complex at Stadium & University, Albuquerque, New Mexico (1-m resolution)

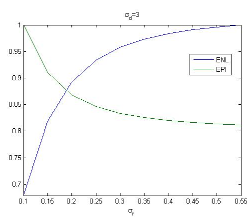


Fig. 2: The variation of normalized ENL and normalized EPI with σ_r

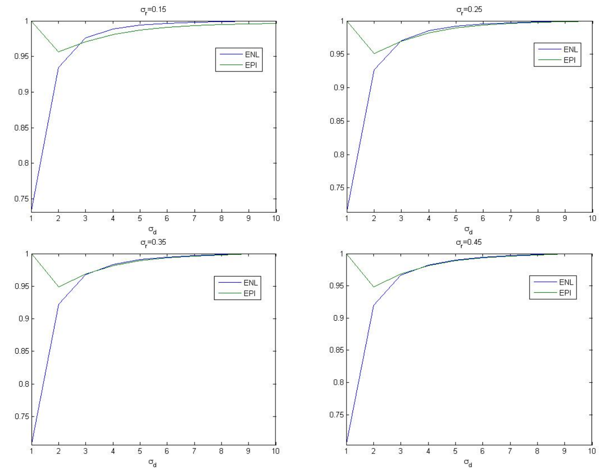


Fig. 3: The variation of normalized ENL and normalized EPI with σ_d

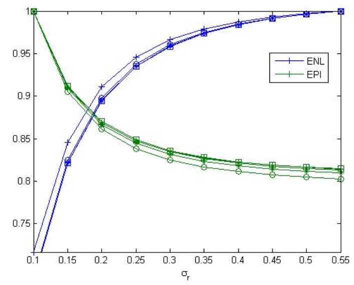


Fig. 4: The variation of normalized ENL and normalized EPI with σ_r . '+', 'O', '*', 'x' and '□' indicate σ_d =1,2,3,4,5, respectively.

To region II, Fig.4 illustrates the variation of normalized ENL and normalized EPI with σ_r when N=5 and σ_d =1, 2, 3, 4, 5, respectively. Fig.4 demonstrates the intersection points of ENL and EPI tend to converge to a limit point that is the best σ_r .

Based on analyses above, we present a modified bilateral filter as follows:

1) For bilateral filtering half-window N, initialize σ_d with $\lfloor 0.75 \times N \rfloor$, set the interval of σ_r (for instance, [0.1, 0.55]), calculate the σ_{ri} (i=1, 2, … n);
2) For every σ_{ri} , apply BF to the normalized image M0, the result denoted by M1, and calculate the normalized ENL and normalized EPI of M1, respectively;
3) Calculate the mean of all σ_{ri} satisfying the condition (5), noted as σ_{r_best} ;
4) Configure the parameters $\sigma_d = \lfloor 0.75 \times N \rfloor$ and σ_{r_best} , apply the BF to M0, filtering result denoted by M2;
5) With the parameters $\sigma_d = \lfloor 0.75 \times N \rfloor$ and $\sigma_{r\_best} / 2$, apply the BF to M2 twice, get the end result.

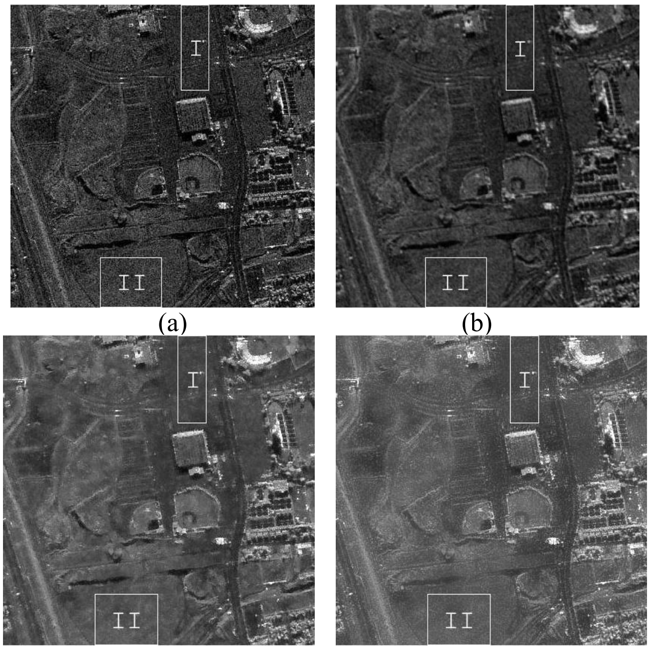
Because the σ_{r_best} and σ_{d_best} are the approximate, to get the better result, post-processing is necessary. Step 5 realizes the post-processing.

4. Experiments and Conclusion

We compare the Lee filtering, BF and MBF de-speckling to region I and II in Fig.1. The Lee filtering takes the size of window 5×5. The BF and the MBF take the N=11, σ_d =7, the interval of σ_r is [0.1, 0.55], and n=10. The Fig.5 illustrates the filtering results.

From the Fig.5, the visibility of (d) is the best.

Table.1 illustrates the compare of quantitative for the filtering results. From the table.1, the modified bilateral filter is superiors to Lee filtering and the bilateral filter in [11] on smoothing images and preserving edges.



(a) (b) (c) (d)

Fig. 5: De-speckling results of different method. (a) original image, (b) Lee filtering , (c) bilateral filtering, (d) modified bilateral filtering

Table 1: Compare of quantitative for the filtering results

Methods	ENL		EPI	
	Region I	*Region II*	*Region I*	*Region II*
Input	10.5227	6.7778	1	1
Lee	24.3319	23.3315	0.3392	0.3540
BF	83.1106	40.5922	0.3444	0.3643
MBF	**101.7162**	**41.2586**	**0.4076**	**0.4937**

This paper analyzed the variation of normalized ENL and normalized EPI with σ_d and σ_r , improved the parameters estimation method of [11] based on the idea in [14], presented a modified bilateral filter. The experiments show the MBF is superiors to the BF on smoothing images and preserving edges, and more visibility. But, the best σ_r and σ_d are still approximate, the optimal estimation method needs to be further study.

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