Collaborative filtering technique for SAR image speckle noise suppression

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***Abstract*— collaborative filtering is a technique used for image restoration among noise and distortions. Based on the fact that an image content has a locally sparse representation in transform domain. Technique employs a non-local modeling of image by collecting similar 2D image patches into 3D groups. The so-called collaborative filtering applied on such a 3D groups is realized by transform domain shrinkage and Wiener filtration. In this work, we implement collaborative filtering algorithm and test it on Synthetic Aperture Radar (SAR) imagery. The experimental results will be presented.**

Keywords*— *non-local filtering, despeckling, SAR

INTRODUCTION

Speckle noise is a common phenomena in all coherent imaging systems like SAR imagery. The source of this noise is attributed to random interference between the coherent returns. Issued from the numerous scatterers present on a surface, on the scale of a wavelength of the incident radar wave. Speckle noises often an undesirable, thus speckle filtering is a critical pre-processing step for detection, classification and optimization. Classical SAR speckle removal or reducing techniques are mainly divided into two categories: multi-look integration and post-image formation methods. Multi-look techniques consist of dividing the bandwidth of the azimuth spectrum of the radar image into L segments called looks forming L independent images [1]. This method decrease the speckle but degrading the image resolution. Post image methods usually have the limitations regarding resolution degradation and smoothing of uniform areas. The most common among the lasts is the Frost filter method [2]. Novel filter based on a wavelet approach have been proposed to overcome the limitations of the classical methods.

Collaborative filtering is the name of block-matching for three dimensional (3D) grouping and filtering procedure. It is realized stepwise, firstly finding similar image patches to the reference patch and then grouping them all together into 3D block; secondly making 3D linear transformation of the 3D block; thirdly manipulating transform spectral coefficients (e.g. by shrinking wisely) to suppress / reduce image noise / distortions; and lastly making an inverse 3D transformation giving block-wise estimates in the image domain. This 3D filter therefore filters out simultaneously all 2D image patches in the 3D block.

In this way, collaborative filtering reveals finest details shared by the grouped patches while suppressing the noise. The filtered patches are then returned to their original positions. Since these patches overlap, many estimates are obtained which need to be combined for each image pixel. Aggregation is a particular averaging procedure used to take advantage of this redundancy. A significant improvement in quality is achieved in the second iteration of a collaborative filtering algorithm, where instead of point-wise filtering we tend to multipoint filtering. The partially cleaned image in the first iteration is then used to estimate the parameters of a further denoising step based on Wiener filtering.

This works almost perfectly for an optical images where we deal with information content disrupted by additive white Gaussian noise (AWGN) and space-invariant fixed point-spread function (PSF). However in Synthetic Aperture Radar (SAR) imagery, because of coherent nature of radar waves, and the subsequent coherent processing, SAR images are corrupted by strong specific noise-like disruption, called “speckle”. What’s more, the “speckle” is modeled as a multiplicative noise.

These fundamental differences between optical and SAR images, forces a modifications of collaborative filtering algorithm to adapt to the existing type of distortions occurring in real SAR imagery. To circumvent this problem, a homomorphic transformation is typically applied on the image beforehand, so to get additive noise e.g. transformation into logarithmic scale. As an alternative, one can avoid the “log-transform” altogether, and model instead the data as affected by signal-dependent additive noise.

COLLABORATIVE FILTER

Data Blocks

Following is presented the algorithm evaluated for the collaborative filter

- The image is divided in square blocks; the blocks are chosen comparing with reference ones.
- The 3D blocks are composed with a variable number of blocks matching with the reference one.
- The formed 3D blocks are 3-D transformed and the noise attenuating is obtained by a hard-thresholding.
- This method is optimal if all of the 2d blocks forming the 3D block are exactly alike. The filter is performed on the 3D blocks and the 2D blocks filtered are replaced in their original location.
- the 2D blocks cant overlap, so the overlapping blocks are wisely aggregated on the overall image.
- The obtained image is divided in square blocks composing the 3D blocks as previously.
- The formed 3D blocks are 3-D transformed and the noise attenuating is obtained by a Wiener filtering.
- The replacement of the 2D blocks is made as previously

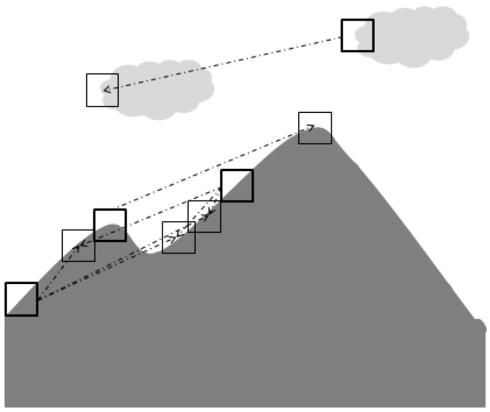

Fig. 1. An example of block matching, with (bold edges of) reference blocks and (thicker edges of) similar ones

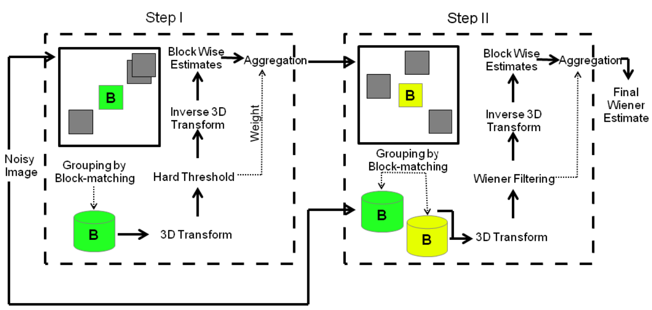

Fig. 2. Collaborative filtering block diagaram

EQUATIONS OF THE FILTER

The noisy image considered can be modeled as follows:

$$z(x) = \sigma(x) + \eta(x) \qquad (1)$$

where $z : X \rightarrow \Re$ and $x \in S \subset X$ while $\sigma(x)$ and $\eta(x)$ are respectively the true image and the noise,

Collaborative filtering algorithm is then applied to SAR image, provided that a homomorphic transform of the data is taken beforehand, the log operation changes the data dynamics and, therefore, the distances among patches [4]. To avoid change of dynamics we scale an image according to following formula:

$$D(x) = 10 * log(I(x))$$

$$z(x) = G * \left(\frac{D(x) - \min(D(x))}{\max(D(x)) - \min(D(x))} \right) \qquad (2)$$

where $I(x) = \sigma(x)\eta(x)$ is an intensity image; $D(x)$ is log intensity image; G is desired dynamic range.

1st Step

Denoting with Z_x the block of a fixed size where x in the top-left corner it is possible to find the distance between two blocks from the norm in l2 as follows:

$$d(Z_x, Z_{xr}) = \frac{\|Z_x - Z_{xr}\|_2^2}{(N_1^{ht})} \qquad (3)$$

where $\left(N_1^{ht}\right)$ is the block size used in Step 1

In order to avoid the problems due to erroneous block matching it is used a method illustrated in bibliography [1] which in this work has been tested on SAR images.
The distance between blocks is calculated using a hard threshold as follows:

$$S_{xr}^{ht} = x \in X : d(Z_x, Z_{xr}) \leq \tau_{match}^{ht} \qquad (4)$$

where τ_{match}^{ht} is the maximum distance for which two blocks are considered similar.
Once the S_{xr}^{ht} is calculated it is possible to form the 3D array on which the collaborative filtering operates in the 3D transform domain. The effective noise attenuation obtained by hard-thresholding, followed by inverse transform that yields a 3D array of block-wise estimates:

$$Y_S^{ht} = \Gamma_{3D}^{ht^{-1}}\left(\gamma_{3D}^{ht}\left(Z_S\right)\right) \qquad (5)$$

where γ_{3D}^{ht} is the hard-threshold operator with threshold $\lambda_{3D}\sigma$, $\Gamma_{3D}^{ht^{-1}}$ is the normalized 3D linear transform and Z_S the 3D array noisy blocks.

2nd Step

The distance between blocks it is calculated using a hard threshold as follows:

$$S_{xr}^{ht} = x \in X: d(Z_x, Z_{xr}) \le \tau_{match}^{wien} \tag{6}$$

where the maximum distance for which two blocks are considered similar is τ_{match}^{wien}

The Wiener filter and the inverse transform produce:

$$Y_S^{wien} = \Gamma_{3D}^{wien^{-1}}\left(W_{3D}^{wie}\left(Z_{Swien}\right)\right) \tag{7}$$

where Z_{Swien} is the 3D Array noisy blocks, $\Gamma_{3D}^{wien^{-1}}$ is the 3D transform coefficient, W_{3D}^{wie} are the Wiener shrinkage coefficients.

To compute the basic and the final estimates of the true-image we performed weighted averaging at those pixel positions where there are overlapping block-wise estimates as discussed in [1].

At the end of whole processing image has to be rescaled back to its original dynamic range (2).

RESULTS

In this section are presented the results of the routine over SAR image with different testing sets. The image used is a SAR image of Dresden, Germany from TerraSAR-X satellite (level 1B product, with direct polarization channel VV). The image showed in figure 2 presents different scenario like a lake(a), rural area(b), river(c), bridge(d), town(e), airport(f). Those are the most common scenario of the Earth looking SAR image.

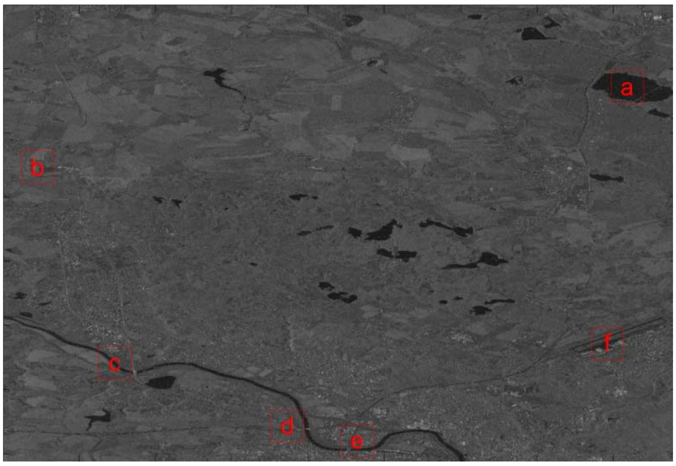

Fig. 3. Analyzed area of Dresden - Germany; TSX1_SAR__MGD_RE___SM_D_SRA_20080204T165156_20080204T165200

Following are presented the results, the column indicated with “Pad” is the half search window size (in pixels) in both steps, “Mb” the size of patch / block (in pixels) in both steps, “Step” is the number of skipped pixels to individuate the next block, “NMb” the number of similar blocks in the 1st step, “NMbW” the number of similar blocks in the 2nd step, while ENLf and ENLi, are respectively the equivalent Number of Looks for the filtered image and for the original image [5]; SSI and SMPI are the Speckle suppression index and Speckle Suppression and Mean Preservation Index [6].

TABLE I. OBSERVED AREA: LAKE (a)

Tuned Parameters					Estimated Values			
Pad	**Mb**	**Stp**	**NMb**	**NMbW**	**ENLf**	**ENLi**	**SSI**	**SMPI**
8	4	1	8	16	16.12	6.14	0.62	40.62
8	8	3	8	16	12.55	6.14	0.70	37.13
16	8	3	16	32	14.63	6.14	0.65	38.88
32	8	3	32	64	17.48	6.14	0.59	39.53
32	8	5	32	64	17.67	6.14	0.59	39.42
32	16	7	32	64	14.33	6.14	0.65	38.43

TABLE II. OBSERVED AREA: RURAL AREA (b)

Tuned Parameters					Estimated Values			
Pad	**Mb**	**Stp**	**NMb**	**NMbW**	**ENLf**	**ENLi**	**SSI**	**SMPI**
8	4	1	8	16	30.75	6.92	0.48	751.92
8	8	3	8	16	21.36	6.92	0.57	767.56
16	8	3	16	32	27.71	6.92	0.51	756.29
32	8	3	32	64	35.22	6.92	0.45	724.05
32	8	5	32	64	35.39	6.92	0.44	724.50
32	16	7	32	64	25.64	6.92	0.52	767.20

TABLE III. OBSERVED AREA: RIVER (c)

Tuned Parameters					Estimated Values			
Pad	**Mb**	**Stp**	**NMb**	**NMbW**	**ENLf**	**ENLi**	**SSI**	**SMPI**
8	4	1	8	16	33.01	5.12	0.41	295.99
8	8	3	8	16	28.49	5.12	0.44	285.77
16	8	3	16	32	41.07	5.12	0.37	271.66
32	8	3	32	64	49.17	5.12	0.33	272.97
32	8	5	32	64	48.81	5.12	0.34	278.00
32	16	7	32	64	37.84	5.12	0.38	282.04

TABLE IV. OBSERVED AREA: BRIDGE (d)

Tuned Parameters					Estimated Values			
Pad	**Mb**	**Stp**	**NMb**	**NMbW**	**ENLf**	**ENLi**	**SSI**	**SMPI**
8	4	1	8	16	26.42	5.19	0.46	427.36
8	8	3	8	16	21.13	5.19	0.52	438.41
16	8	3	16	32	24.66	5.19	0.48	441.09
32	8	3	32	64	29.11	5.19	0.43	439.32
32	8	5	32	64	28.55	5.19	0.43	440.56
32	16	7	32	64	21.54	5.19	0.50	454.52

TABLE V. OBSERVED AREA: TOWN (e)

Tuned Parameters					Estimated Values			
Pad	Mb	Stp	NMb	NMbW	ENLf	ENLi	SSI	SMPI
8	4	1	8	16	7.03	2.40	0.58	1869.08
8	8	3	8	16	5.68	2.40	0.64	1917.21
16	8	3	16	32	6.52	2.40	0.60	1992.26
32	8	3	32	64	7.46	2.40	0.56	2025.38
32	8	5	32	64	7.50	2.40	0.56	2026.19
32	16	7	32	64	6.05	2.40	0.62	2030.54

TABLE VI. OBSERVED AREA: AIRPORT (f)

Tuned Parameters					Estimated Values			
Pad	Mb	Stp	NMb	NMbW	ENLf	ENLi	SSI	SMPI
8	4	1	8	16	34.67	5.43	0.41	178.98
8	8	3	8	16	31.60	5.43	0.43	166.71
16	8	3	16	32	42.99	5.43	0.37	165.39
32	8	3	32	64	49.63	5.43	0.35	172.08
32	8	5	32	64	48.12	5.43	0.35	174.30
32	16	7	32	64	40.94	5.43	0.38	170.39

Following are addressed the figure of the results using the collaborative filtering algorithm on part of the Dresden SAR image.

Fig. 4. Original image section

Fig. 5. Image section after collaborative filtering

CONCLUSIONS

In this work has been presented the realization of collaborative filtering algorithm for Speckle reduction in SAR images. The first and second steps have taken the advantage respecting the standard procedure of shifting the image dynamic so that any image react in a similar way to the filter, depending on the backscattering of the area. The distances from the blocks has been fixed and also the threshold of the noise. The algorithm is non-local adaptive non parametric filtering. It is possible to see from the tables the algorithm increases the number of looks (from TABLE I to TABLE VI); the SSI in the best cases reaches 0.33, which indicates a good filtering function; while SMPI varies depending on the area and can be useful to indicate of which area and which kind of backscattering is being individuate. Future studies can be made on improvement of the filtering introducing better block matching method, different noises models, different spatial transforms.

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