FILTERING OF REMOTE SENSING IMAGES FORMED BY SYNTHETIC APERTURE RADAR

1 Ponomarenko N.N., ¹Lukin V.V., ¹Abramov S.K. and ² Egiazarian K.O.

¹ National Aerospace University, Kharkiv, Ukraine E-mail: [uagames@mail.ru,](mailto:uagames@mail.ru) lukin@ai.kharkov.com ² Tampere University of Technology, Tampere, Finland E-mail: karen@cs.tut.fi

Abstract

Basic properties of synthetic aperture radar (SAR) images are determined by many different factors that include real radar antenna size and its pattern, synthetic aperture size, used windows and spatial sampling, number of looks and other imaging conditions, etc. Due to several factors, an obtained image is degraded by speckle and this speckle occurs to be spatially correlated. Below we propose a method to cope with spatially correlated noise based on discrete cosine transform (DCT) filtering adapted to an image at hand. Simulation results demonstrating that due to exploiting the obtained estimates it is possible to improve filter performance by 1…2 dB in terms of PSNR are presented. Real life examples of SAR image processing are given as well.

Keywords: synthetic aperture radar, image, speckle, filter.

1. INTRODUCTION

Potentially high spatial resolution in SAR imaging is provided due to a large relative (with respect to wavelength) size of synthesized aperture whilst real (physical) antenna mounted on-board of an airborne or spaceborne carrier might have a rather small size. Resolution in azimuth plane cannot be smaller than physical antenna half-length and is mainly determined by SAR operation mode, synthesized antenna size, a window if it is used, and atmosphere turbulence [1, 2]. Meanwhile, formed images suffer from an inherent phenomenon called speckle that arises due to coherent mode of received signal processing [1] and prevents image interpreting.

Speckle can be suppressed in different ways [1, 3]. The most common are forming an image in multi-look mode and spatial filtering of obtained remote sensing data. The factors that restrict a set of applicable filters are non-Gaussian multiplicative nature of speckle and its spatial correlation. Spatial correlation of speckle can be due to processed data oversampling, usage of a weighting window, atmosphere heterogeneity [2, 4]. Note that statistical and, especially, spatial correlation characteristics of speckle in a given image can be unknown in advance. Obtaining of such data in interactive mode is a labor-consuming task.

This makes difficult to provide efficient speckle removal. There are, at least, two reasons behind this. First, one often needs fast, blind and accurate estimation of noise statistics. Second, many known filters [3] do not take into account spatial correlation of noise although it is worth doing. Therefore, below we propose methods for blind evaluation of multiplicative

noise variance and estimation of spatial spectrum of speckle. This information is further used in adaptive filtering of SAR images based on DCT in overlapping blocks. This data processing tool allows incorporating the obtained estimates easily and in effective manner.

2. BLIND ESTIMATION OF NOISE CHARACTERISTICS

Usually it is assumed that multiplicative noise is the main factor degrading SAR image quality [1, 3, 4]. Really, speckle is the dominant factor although additive noise can be present as well. Thus, simultaneously with blind estimation of speckle noise variance σ_{μ}^{2} it is desirable to evaluate variance of additive noise σ_n^2 and to decide is it worth taking additive noise into account. Then one needs a more complicated technique than that one proposed in [7] which is intended for estimating only σ_{μ}^2 . Fortunately, a method for blind estimation of both σ_{μ}^2 and σ_{n}^2 has been designed recently [6]. Its application to 8-bit SAR images kindly offered to us by the Kalmykov Center of Earth Radiophysical Remote Sensing (Kharkiv, National Academy of Science and National Space Agency of Ukraine) shows that σ_n^2 is of the order 10…20. This means that if, e.g., $\sigma_{\mu}^2 \approx 0.15$, then the influence of multiplicative and additive noise is comparable for image fragments with local mean $I_{loc} \leq 20$, that is, e.g., for SAR image fragments corresponding to water surfaces (see the SAR image in Fig. 1,a, the Dnieper river region).

Blind estimation of σ_{μ}^2 and σ_{n}^2 can be carried out by robust fitting of straight line into a scatter-plot of local estimates of noise variance in blocks of fixed size *N*x*N* where horizontal axis of the scatter-plot corresponds to squared local mean. An example of such a scatter-plot and line fitting obtained for the SAR image in Fig. 1,a is presented in Fig. 1,b. The obtained estimates are $\hat{\sigma}_n^2 = 14$ and $\hat{\sigma}_n^2 = 0.15$. Note that the block size has been selected 7x7 to account for possible spatial correlation of noise [8]. Besides, pre-segmentation of the image has been performed in order to remove abnormal local estimates of variance to further improve estimation accuracy [8].

After getting the estimates $\hat{\sigma}_n^2$ and $\hat{\sigma}_\mu^2$, it becomes possible to find the blocks of size N_{DCT} x N_{DCT} that can be considered homogeneous. For this purpose, for each image *nm*-th block local variance $\hat{\sigma}_{loc}^2(n,m)$ is calcu-

lated as $\hat{\sigma}_{loc}^2(n,m) = \sum_{n=N}^{n+N_{DCT}} \sum_{l,j}^{m+N_{DCT}} (I_{ij} - \overline{I}_{nm})^2 / (N_{DCT}^2 - 1),$ $\hat{\sigma}_{loc}^2(n,m) = \sum_{i=n}^{n+N_{DCT}} \sum_{j=m}^{m+N_{DCT}} (I_{ij} - \overline{I}_{mn})^2 / (N_{DCT}^2)$ local variance $\hat{\sigma}_{loc}^2(n,m)$ is calcu-
= $\sum_{i=n}^{n+N_{DCT}} \sum_{j=m}^{m+N_{DCT}} (I_{ij} - \overline{I}_{mn})^2 / (N_{DCT}^2 - 1),$ $n + N_{DCT}$ $m + N_{DCT}$ $\overline{I}_{nm} = \sum_{n+N_{DCT}}^{n+N_{DCT}} \sum_{i,j}^{m+N_{DCT}} I_{ij} / N$

/ $N_{\scriptscriptstyle D}^2$ $n_{nm} = \sum_{i=n}^{\ } \sum_{j=m}^{\ } I_{ij} / N_{DCT}^{2}$ $= \sum_{i=n}^{n+N_{DCT}} \sum_{j=m}^{m+N_{DCT}} I_{ij} / N_{DCT}^2$ where *n* and *m* define a block upper left corner, I_{ij} , \overline{I}_{nm} are the *ij*-th image pixel

value and *nm*-th block local mean, respectively. Then,

Fig. 1. A fragment of real-life SAR image (a), the obtained scatter-plot of local estimates of noise variance vs squared local mean (b), the estimated 2-D autocorrelation function of spatially correlated noise (c)

if $\hat{\sigma}_{loc}^2(n,m) \leq 1.3(\hat{\sigma}_n^2 + \hat{\sigma}_\mu^2 \overline{I}_{nm}^2)$, an *nm*-th block is considered homogeneous and it is used for further estimation of spatially correlated noise spectrum. Note that noise spectrum can be obtained in traditional spatial Fourier domain as well as in DCT domain. Traditional 2-D spatial autocorrelation function (ACF) is presented in Fig. 1,c for the homogeneous area of size 32x32. This ACF is not a thumb-like function, main lobe widths in horizontal and vertical main cross-sections are different. There are no obvious side lobes. Thus, spatial correlation exhibits itself only for image neighboring pixels. This allows suppressing such spatially correlated noise using image processing using DCT based filtering in limited size blocks where the normalized DCT spectrum $D_{norm}(p,q)$ is already determined from the set of blocks classified as homogeneous (see details in [6]).

3. ADAPTIVE DCT BASED FILTERING

Adaptive DCT based filtering is carried out in N_{DCT} *x* N_{DCT} blocks where N_{DCT} is usually set equal to 8 to provide fast computations. To provide better noise suppression [9], overlapping blocks are to be used. In each block, forward DCT is performed first with obtaining $D(n, m, p, q)$ and a local thresholds' set is caltaining $D(n, m, p, q)$ and a local thresholds' set is calculated as $T(n, m, p, q) = \beta D_{norm}(p, q) (\hat{\sigma}_n^2 + \hat{\sigma}_\mu^2 \overline{I}_{nm}^2)^{1/2}$ where β is commonly set equal to 2.6 (it is also possible to use a block median instead of block mean). Then, a set of thresholded DCT coefficients is obtained as $D_r(n, m, p, q) = 0$ if $|D(n, m, p, q)| < T(n, m, p, q)$ and $D_t(n, m, p, q) = D(n, m, p, q)$ otherwise (DC coefficient $D(n, m, 0, 0)$ is not subject to thresholding). Inverse DCT is applied to the obtained set of $D_t(n, m, p, q)$. Then one gets image filtered values for a given block pixels. If blocks overlap, final filtered values for an image are obtained by simple averaging of blocks' filtered values each given pixel belongs to.

Note that the difference with respect to conventional DCT based filtering of radar images is that for the latter one the thresholds are set as $T_c(n,m) = \beta \hat{\sigma}_{\mu} \overline{I}_{nm}$. Let us compare the results for the conventional and the proposed filtering methods. The output image for the conventional method is represented in Fig. 2,a, whilst for the proposed method (that takes into account additive noise component and spatial correlation of noise) the output image is shown in Fig. 2,b. As it is seen, the speckle noise is suppressed well in both images. More detailed analysis has demonstrated that for the proposed method variance of residual fluctuations in image homogeneous regions is almost twice smaller than for the conventional DCT based filter. This positive effect is due to accounting for both additive noise component and spatial correlation. For image homogeneous regions with relatively small local mean like water surface, both factors have approximately the same impact.

On the contrary, in image homogeneous regions with rather large local mean like agricultural fields, accounting for spatial correlation of noise contributes more into filtering efficiency improvement. Besides, better edge/detail/texture preservation is provided for the proposed method. This is clearly seen from comparison of the output images. Note that the obtained information on noise characteristics allows detecting sharp edges and high contrast details. Then, instead of DCT based filtering that partly smears such fragments it becomes possible to locally apply filters able to preserve edges and details better.

We have also carried out simulations for artificial images corrupted by spatially correlated noise with 2-D autocorrelation function similar to that one in Fig. 1,c. It has been established that due to taking into account spatial correlation of noise and thanks to setting frequency dependent thresholds it is possible to improve output images both in terms of traditional metrics like PSNR, MSE by about 1...3 dB and according to visual quality metrics [10].

Fig. 2. Output images for the conventional (a) and the proposed (b) DCT based filters

4. CONCLUSIONS

It is demonstrated that noise in SAR images is spatially correlated and it is worth taking this into account at filtering stage. Moreover, the filtering method based on DCT in blocks with setting frequency and local mean dependent thresholds is proposed. Its efficiency is tested for real life image (testing on artificial images has been carried out earlier [10]). As shown, the proposed method produces more efficient noise suppression and better edge/detail/texture preservation.

It is also demonstrated that variances of both multiplicative and additive noise can be estimated in a blind manner (i.e., automatically). Appropriate accuracy is provided under two conditions. First, at least 15…20% of image blocks are to be homogeneous. Second, 7x7 or even 9x9 blocks have to be used for obtaining local estimates of image variance in the case of possibly spatially correlated noise.

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