AUTOMATIC ESTIMATION OF THE NOISE VARIANCE IN SAR IMAGES FOR USE IN SPECKLE FILTERING

Giovanni Ramponi, Raffaele D'Alvise

DEEI, University of Trieste
via Valerio 10, 34127 Italy
e-mail ramponi@univ.trieste.it

Cecilia Moloney

Faculty of Engineering and Applied Science
Memorial University of Newfoundland
St.John's, NF, Canada, A1b 3X5
e-mail moloney@engr.mun.ca

ABSTRACT

Synthetic Aperture Radar *(SAR)* is an active imaging system widely used in remote sensing applications. *SAR* systems are characterized by their high image resolution and all-weather operating ability, but suffer from the notorious speckle noise [1], which is a random multiplicative phenomenon that results from coherent imaging. In this paper we propose several heuristic methods for the estimation of the speckle noise variance. They can also be applied in other cases where multiplicative noise is present, and do not need specifically tuned input parameters.

1. INTRODUCTION

SAR systems are characterized by a high image resolution but suffer from the notorious speckle noise. The model used to study the statistical properties of the speckle is multiplicative as suggested in [2, 3]. In this model, the available image y is obtained as $y = xn$, where x is the ideal uncorrupted image and n is a white noise random field with unity mean, $E[x] = 1$, and standard deviation $Std(n) = \sigma_n$. The original image x and the noise are assumed to be independent. Simple manipulations show that in the case of homogeneous areas, where the signal component can be considered constant and the image variation is attributable to noise only, the standard deviation of the speckle noise is given by [2]:

$$Std(n) = \frac{Sdt(y)}{E[y]} \quad (1)$$

The latter ratio is usually called the coefficient of variation R. The value of R indicates the quality of the available image and can be used as a parameter to control the behaviour of various operators. For example, the classical Lee operator [2] is a local statistics-based filter which modifies its characteristics according to the noise variance. In another case, knowledge of the properties of the noise is hypothesized in performing a comparison among different filtering algorithms based on various criteria [4].

In this paper we introduce three new techniques for the estimation of R. Advantages of these techniques are that they do not need specific parameter tuning, they can operate in presence of additive noise and they can work on images which contain many detail areas. The proposed methods first extract from the image a set of blocks that can be considered homogeneous, then they estimate the local Std and the mean from each block. The R value is the slope of a linear regression applied to the extracted pairs of data.

2. MANUAL AND AUTOMATIC ESTIMATION

A conventional technique used to estimate the Std of the speckle noise consists first in the manual selection of a set of image blocks which contain no significant details or textures, and which can thus be described as regions of homogeneous reflectance corrupted by noise. Then the sample estimates of the local standard deviation σ and of the mean value μ of a block are obtained from those extracted; each couple of values represents a point in a scatter plot. In the case of selected blocks which belong to homogeneous areas, the scatter points are distributed approximately around a straight line whose slope can be determined via a linear regression [5] and which corresponds to R. This method is effective but requires human intervention and is prone to subjective errors. Moreover, for a human operator it is difficult to locate small homogeneous blocks; hence the image should contain large homogeneous areas. For our experiments, manual estimation has been performed on two real 4-look SAR images called *Stanwick* and *Ext*; the resulting values respectively are 0.239 and 0.278.

Several heuristic methods for automatically estimating *R* can be found in the literature. In [3] Lee proposes two techniques; the former is the Radial Sector **(RS)** method and the second is the Partitioned Least-Squares Fit **(PLSF)** method. In both cases, a *SAR* image is divided into small blocks (4×4 or 6×6 pixels), the scatter plot is obtained and the slope of a straight line crossing the main cluster of

points is determined.
In the RS method, a radial sector of size $\Delta\theta$ is defined in the scatter plot. The slope of the sector is varied and the estimated value of R is the slope of the sector which contains the maximum number of scatter points. The angular step between two adjacent positions of the sector is set to $\Delta\theta/3$. This method can produce good results but the output depends on a proper choice of $\Delta\theta$. For example, if an image has a high concentration of scatter points associated with detail areas, the chosen sector tends to have the slope of this area.
In the PLSF method the scatter plot is partitioned into horizontal classes by a uniform segmentation of the mean axis. For each class a vector of standard deviation elements is obtained. In the classes where the number of elements is greater than 10, a histogram is computed; the histogram maximum is chosen as the Std of the homogeneous blocks in the partition. In this way, a couple of values is obtained for each class, representing its mean and the Std of its elements. A weighted linear regression is applied to such values.

3. THE PROPOSED TECHNIQUES

3.1. The Baseline (BL) method

When the scatter plot is obtained from blocks of large size (10×10 or greater) it reveals a particular aspect. We can easily recognize what will be called in the following the *noise baseline*, that is a distribution of blocks located in the lower left part of the cloud of points, approximately along a straight line. This group of blocks represents parts of the image in which the original signal is uniform, and the sample variance is only due to the noise. The estimation of R is easy if we can consider only the points belonging to the baseline. The algorithm we use has some similarities with Lee's PLSF method. It first splits the points in two groups: the first one represents highly textured or detail blocks, the second one represents blocks where almost homogeneous image data are present. To achieve this partition a linear best fit of the overall set of points is performed. All the blocks represented by points above this line are discarded. The μ value of each of the remaining blocks is rounded to the nearest integer, and for each rounded mean value a vector $\overline{v}$, constituted by standard deviation elements, is obtained. The baseline is formed by the set of $(\overline{\mu}, min(\overline{v}))$ couples computed over those classes with more than ten same-mean blocks. Finally, a linear best fit is performed using the baseline data set; R is obtained from the slope of the regression line. The main drawback of this method is the bias of the returned value in comparison to the real one. Generally the estimated value is smaller than the one obtained from the manual method, due to the usage of the min operator.

3.2. The Three Best Fits (3BF) method

In the second proposed method the scatter plot is divided into three parts to obtain the homogeneous blocks: in principle, the first portion is composed of detail blocks, the second one of texture and the third one only of noise. Two successive linear regressions are performed on the data set, to select the noise class. The first best fit is computed on the whole set of data. It divides the plot in two classes: the first one, constituted by the points above the regression line, is labelled as detail; the second one is formed by the textural and noise elements. Then, the first set of points is removed and a new best fit is performed; in this manner the residual elements are divided in texture and noise. As in the previous method, the R parameter is evaluated by a linear best fit on the blocks labeled as noise only. An advantage of this method is its computational simplicity.

3.3. The Correlation (COR) method

The couples of estimated values (μ, σ) obtained from homogeneous blocks are strongly correlated. The correlation method selects homogeneous blocks by successively removing the points which are not correlated with others. A linear best fit is computed over the scatter plot; then the algorithm determines which point is farthest from the straight line of the best fit and removes it. In fact, this point can be considered as the least correlated element in the set of the scatter plot points. A new best fit is then computed and the iteration is repeated. The algorithm terminates if a test condition is verified. As with the previous methods, a linear regression is performed on the estimated (μ, σ) couples of values to obtain an estimate of R from the extracted blocks.
Two kinds of condition-test are used. In the first one, after removing the farthest element the correlation parameter is calculated from the remaining data (x_i, y_i):

$$\rho = \frac{\sum_i (x_i - \mu_x)(y_i - \mu_y)}{\sqrt{\sum_i (x_i - \mu_i)^2 \sum_i (y_i - \mu_y)^2}} \qquad (2)$$

where μ_x and μ_y are the mean values of the set elements x_i and y_i. If the correlation coefficient is close to 1, i.e. it is larger than a suitably defined threshold level ρ_{lim}, the procedure is stopped. Note that the threshold level is a general input parameter and it does not need a particular setting for different SAR images. In the second case the iterations are terminated when the distribution has a symmetric shape with respect to the regression line. To detect this condition, the last M deleted elements are stored in a vector $\overline{v}$, and a new binary vector $\overline{b}$ is defined. In the i-th position of $\overline{b}$ a 1 or a 0 is present if the i-th element of $\overline{v}$ is above or below the latest computed regression line respectively. If the number of 1's differs from the number of 0's by less than 2, the symmetry condition is reached.
It must be noted that in the first iterations only points above

Images	MAN	RS	PLSF	BL	3BF	COR
Stanwick	0.239	0.249	0.367	0.247	0.233	0.253
Ext	0.278	0.287	0.318	0.284	0.265	0.269

Table 1: Estimated values of R

Images	RS	PLSF	BL	3BF	COR
Stan1	0.306	0.371	0.299	0.265	0.282
Stan2	0.268	0.338	0.257	0.244	0.262
Stan3	0.268	0.359	0.325	0.251	0.258
Stan4	0.230	0.377	0.268	0.224	0.227
Stan5	0.249	0.332	0.256	0.235	0.249
Stan6	0.249	0.337	0.326	0.226	0.235
m.r.e.	0.279	0.579	0.365	0.106	0.178
Var. (10^{-4})	6.54	3.69	10.06	2.40	3.78

Table 2: Sensitivity study.

the scatter plot are removed; the relative distance of the removed elements becomes progressively smaller. After a while the behaviour changes and some of the removed elements are below the regression line. In this situation the distribution is not symmetric, but the vector $\overline{b}$ satisfies the test condition. To avoid early termination of the process both tests are applied in different times. At the beginning the first test is used to remove elements above and below the regression line; then the second test is applied.

4. COMPARISON OF THE METHODS

The performances of the proposed techniques are evaluated and compared using the two 4-look *SAR* images: Stanwick and Ext. The analysis can be divided in four parts: **a)** Comparison of the manual and automatic estimation; **b)** Study of the sensitivity of the methods; **c)** Performances of the estimated value of R used as a parameter for the classic Lee SAR image filter [2]. **d)** Visual study of the extracted blocks using the scatter plot.

In the first case, **a)**, we propose the output value yielded by the various methods. As suggested in [3], the θ value in the RS method is set to 3. Because of the different properties of the algorithms the size of the blocks vary. We used 6×6 elements for the case of RS and COR techniques, 16×16, 8×8 and 4×4 for the BL, 3BF and PLSF methods respectively. In Tab.1 the estimated values are shown. All the measures can be considered a rather good estimation of Std of the speckle noise since the methods return values quite similar to the manually one computed in Section 2. For the Stanwick image the error between the manual and estimated value is minimum using the 3BF method, while for the Ext image the minimum value is obtained with the BL method.

The second analysis, **b)**, studies the sensitivity of the algorithms. Each method is applied to different subimages extracted from the same image: the estimated values should be very similar one to each other. The methods should be independent of the detail characteristics associated with each sub-image analyzed. From the Stanwick image we obtain 6 subimages of size 256×256, called Stan1,…,Stan6 respectively; the R value is estimated on each. Two figures of merit are defined: the variance of each method for the different subimages, and the maximum relative error (m.r.e.) between the automatic and manual estimates of R (see Tab.2). The comparison of the methods reveals differences regarding the stability of their performance. The best algorithm from this point of view is the three best fit 3BF, then we have COR, RS, BL, PLSF respectively.

Using the estimated value of R as an input parameter for the classic speckle Lee filter [2] reveals the quality of the proposed methods and the advantages of the automatic estimation **(c)**. In Fig.1 we show the sample original image

Figure 1: Original 4-look SAR image Ext

Ext, while in Fig.2 we propose its filtered version. We used the estimated Std of the speckle noise returned by the COR method and the size of the mask filter equal to 11×11. As it can be seen, we obtained a strong attenuation of the speckle noise in homogeneous areas, and the preservation of the detail structures. The last analysis, **d)**, shows visually the results of extracting blocks from an image. For each method the different steps of the homogeneous block selection process are indicated in the respective scatter plot. Fig.3a) and Fig.3b) respectively show the results of the RS and PLSF method, in the former, the sector which yields the maximum number of scatter points is evident. Fig.3c) is related to the baseline method (BL); the particular selection of the points which are used in the linear regression, makes the value of R slightly biased. The main problem is that this technique, as it is shown, does not remove points located in the lower part of the scatter plot. Fig.3d) shows

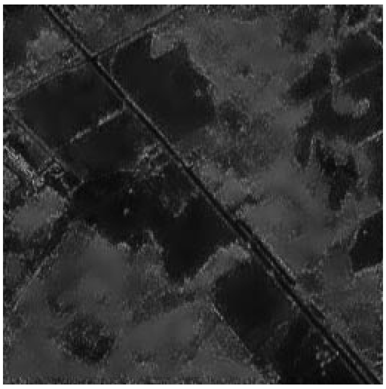

Figure 2: Ext image evaluated by a Lee multiplicative filter

the three best fit method (3BF), which has the overall best performance of the techniques we propose here. The three parts in which the scatter plot is divided are easy to locate. In Fig.3e) we draw the case of the correlation method. The points whose regression line gives the R value are located in a narrow strip, so that the estimated value is very stable and has a narrow confidence interval.

5. ACKNOWLEDGEMENTS

This work has been partially supported by a grant of the University of Trieste and by the Natural Sciences and Engineering Research Council of Canada.

6. REFERENCES

[1] J.W. Goodman, “Some Fundamental Properties of Speckle Noise.”, *J. Opt. Soc. Am.* Vol.66, n.11, pp.1145-1150, Nov 1976.

[2] Jong-Sen Lee, “Speckle Analysis and Smoothing of Synthetic Aperture Radar Images.” *Computer Graphics and Image Processing*, Vol.17, pp.24-32, 1981.

[3] Jong-Sen Lee, Karl Hopper, and Stephen A.Mango, “Unsupervised Estimation of Speckle Noise in Radar Images”, *International Journal of Imaging Systems and Technology*, Vol.4, pp.298-305, March 1993.

[4] Zhenghao Shi and Ko B. Fung, “A Comparison of Digital Speckle Filters”, *Proceedings of IGARSS ’94*, Pasadena, Calif., August 1994.

[5] William Press, Saul A. Teukolsky, William T. Vetterling and Brian P. Flannery, “Adaptive Speckle Filters and Scene Heterogeneity”, *Numerical Recipes in C*, Second Edition, Cambridge University Press, 1992.

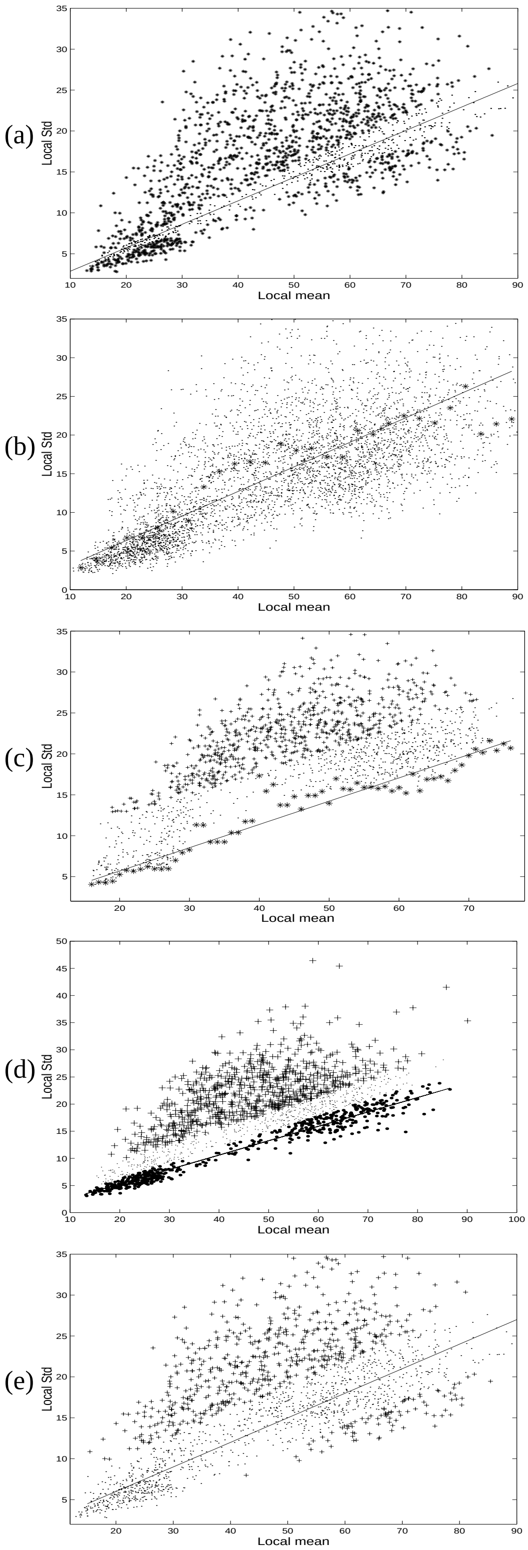

Figure 3: Scatter points selected by the various methods. RF (a), PLSF (b), BL (c), 3BF (d), COR (e)