A PROTOCOL FOR SPECKLE FILTERING OF SAR IMAGES

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Abstract— **Speckle filtering of SAR images that preserves the spatial signal variability (texture and fine structures) remains a challenge. Recently, research activity in this topic has become very active until the appearence of many "new" filters. Filter performance assessment mainly based on visual interpretation, is not effective in revealing hidden limitations of filters. Hence, there is an immediate need for the development of rules which permit more effective assessment. These rules could be also used as the basis for the development of new filters. In this study, a protocol which is based on the state of the art in speckle filtering is introduced. Such protocol, which should not become an obstacle for the advancement of research in speckle filtering, might be updated according to the actual state of the art in the field. Finally, the introduced protocol is used to assess several well-known filters, and to develop a new multiresolution MMSE (i.e. Minimum Mean Square Error) which is much more effective than the classical MMSE filters.**

I. Introduction

Speckle filtering of SAR images while preserving the spatial signal variability (texture and fine structures) still remains a challenge. The nonstationary nature of the underlying signal makes adaptive filters more effective than the spatially invariant filters used extensively in digital image processing [4], [12]. The former filters adapt their processing to the nonstationary scene signals by using a spatially moving window of a fixed size. Two speckle-scene models are generally used: the multiplicative model, and the product model. These models yield two families of filters which might be distinguished: filters based on the multiplicative speckle model which do not use explicitly the statistical distribution of the underlying scene such as the Lee and Frost filters [4], [12], and the Bayesian filters [11], [16] based on the product model which requires, in addition, an a priori statistical model for the underlying scene signal. In practice, the two family filters are applied using a moving window of a relatively small size (7x7 window is the mostly used (see [12]) in order to provide a satisfactory compromise between speckle reduction and preservation of small structures within a tolerable computing time.

In the following, the objective of speckle filtering is considered. In Section III, speckle filtering of nonstationary scene signals is discussed in the context of estimation theory. It is shown that the scene reflectivity can only be retrieved accurately for nonstationary scenes which are locally stationary. Signals which are not locally stationary have to be filtered separately using a priori information. In section IV, the speckle multiplicative noise model, the product model, and the related scene models are analysed with regards to signal nonstationarity. Speckle filtering of locally stationary scenes is discussed in Section V, and the necessity of the use of multi-resolution algorithms for accurate estimation of filter parameters is brought out. Speckle filtering of locally nonstationary scenes is then considered in Section VI. This leads to the introduction of a protocol for speckle filtering in section VII. Finally, the protocol is used to assess theoretically the performance of some well known filters, and to develop a new multi-resolution MMSE filter which is more effective than the classical speckle filters based on the MMSE technique.

II. Objective of speckle filtering

The main objective of speckle filtering is to retrieve the radiometric and spatial scene information "R" from the observed "speckled" SAR measurement "I". "R" is generally the incoherent image of the original scene signal (i.e. scene signal viewed with the incoherent transfer function of the SAR system) [17], [11]. In certain cases, the signal to be retrieved "R" might be the scene signal free from the viewing system transfer function, and the delivered filtered output is named the super resolution image [18]. Deconvolution techniques might be used to reconstruct the scene signal. Such techniques which tend to amplify the high spatial frequency noise are not suitable for the inversion of SAR images of small signal to noise ratios [3]. The scene signal might also be retrieved using the Bayesian inverse problem approach proposed in [1]. Such a technique is very sensitive to the assumed a-priori models, and unrealistic behaviour might be introduced due to an erroneous model [1].

III. Speckle filtering in the context of estimation theory

In both the two cases mentioned above (i.e. incoherent or super-resolution image), speckle filtering remains mainly an estimation problem, and filter development should be performed with respect to certain rules determined by classical estimation theory. Given one realisation of the stochastic process I(t) observed during a finite interval of time, the estimation of the random process parameters can lead to meaningful estimates only if I(t) is ergodic and stationary. Stationarity is required such that the time averages of each process converge to a finite limit. Ergodicity is also required so that the different time averages of each process converge to the same limit: the ensemble average. The process parameters can then be estimated by time (in the image domain spatially) averaging the process over a finite interval of time. In the following, the processes involved in the SAR image modelling are assumed ergodic. Speckle filtering will be discussed in term of signal sationarity-nonstationarity.

Because of the spatial variations of the scene signal, the measured radar signal I(t) is not generally stationary, and the estimations of the filter parameters (such as the mean and coefficient of variation) lead to meaningless values.

In practice, stationarity in mean (the assumption that the mean $E(x)$ does not vary) may be relaxed: all that is required is that $E(x)$ does not change significantly within the observation interval [10]. If such a condition is satisfied by the processes involved in the filtering equation, the nonstationary processes can be considered locally stationary (named "stationary in increments" in [10]), and the parameters required for speckle filtering can be estimated over a moving window in which the processes involved are stationary. This corresponds to the basic idea of the adaptive filtering. The adaptive filter parameters which are estimated locally within a moving window (in which the observed and the scene signals are stationary), vary spatially (with the window position) to cope with the observed and scene signal variations.

IV. Speckle and scene models

A. Multiplicative model for speckle

Under the assumption that the terrain reflectivity R(t) is slowly varying within the resolution cell (i.e. locally stationary within the resolution cell) [27], the multiplicative model states that the observed intensity of the pixel located at t=(x,y) is given by [4], [12]: I(t)=R(t).n(t). The speckle random function n(t) is assumed to be stationary white unit mean χ^2 distributed. As we previously mentioned in a study on speckle filtering of polarimetric data [24], the stationarity assumption for speckle noise is suitable for the following reasons:

- Speckle statistics are constant on the whole scene. They can be accurately estimated, and need to be estimated once for the whole scene.
- The algorithms for filtering of stationary noise are much simpler to implement and less expensive in computing time than the ones developed for nonstationary noise.
- Certain aspects of speckle related to the illuminated scenes (such as the degree of polarization of the scattered wave due [24]) should remain in the filtered image (for a better characterisation of the scene).

B. Scene model for stationary speckle noise

For accurate estimation of signal parameters, the observed signal should be locally stationary. Such condition might be satisfied provided that R(t) is locally stationary (as speckle is stationary). The scene signal and the observed signals are then both stationary in increments, and signal parameters can be estimated accurately within a moving window in which the signals are locally stationary (and ergodic). For a nonstationary scene, signal parameters vary from one window position to another. This leads to parameter estimates which vary spatially with the window position in order to cope properly (and as such to have a better capability of speckle filtering) with the spatial variations of the scene signal. One application of the stationary in increments model is the nonstationary mean nonstationary variance scene model (NMNV) of [11]. It assumes that the scene (and consequently the observed) signals are locally stationary in mean and variance. This model might be presented as as the basis of some well known filters such as the Frost and Lee filters whose parameters are mainly the local mean and coefficient of variation estimates.

C. Speckle-scene product model

The product model, also called the double stochastic model, was used as the basis of the MAP Bayesian one-level (Gaussian [11], and Gamma [15], [19]), and multi-level([1]) filters. The product model was introduced in ([14], [8], [7]) to express the K-distribution, which fits well ocean backscattering [6], as a function of the Gamma distribution whose statistics are easier to estimate [20], [9]. The spatially varying Rayleigh clutter distribution which is conditioned on its gamma-distributed local mean leads to unconditioned PDF which is K-distributed.

The product model is based on a technique developed for characterising nonstationary functions (see [14] for example). The first-order density function of the nonstationary process is treated as a function of random key parameters, and is presented in term of conditional probability density function (pdf). The conditional pdf is averaged over the parameter under consideration to yield an unconditional pdf which is stationary in the parameter of integration even though the original (conditional) pdf is not stationary. An equivalent method was proposed in [21] to transform a nonstationary correlation function to a stationary function named the spatially averaged correlation function. This method was used in [26] to justify the use of the adaptive coherence estimate for characterisation of nonstationary coherence signals.

In contrast to the multiplicative model of (IV.A), the product model of (IV.C) assumes that speckle, which is still locally stationary within a resolution cell (i.e. the multiplicative model condition satisfied), is not stationary in mean within the moving processing window. The mean is supposed to vary from one pixel to another according to a given distribution (Gamma for example). Using the product model, the Bayesian filters transform the nonstationary speckled signal (I(t)) in a locally stationary signal (K distribution of stationary mean and variance for example) within the moving processing window. The parameter estimation is applied in two levels: estimation at the pixel level (for each pixel) of the mean of the χ^2 speckle distribution, and estimation at the window level of the statistics of the mean reflectivity (i.e. the averaged pixel means which corresponds to the Gamma parameter). For meaningful statistical description, the processing window should be large enough to include many samples of the same speckle

χ^2 distribution (for the first-level estimation), and enough samples of the various χ^2 distribution (for the second-level estimation). Therefore, the filtering window size should be larger than the one which might be used under speckle stationarity assumption of section (IV.A).

The result above concerning the classical product model which is a double stochastic model, might be extended to the multiply stochastic model described in [14], [23]. The multiply stochastic is formed by averaging its mean over a first-level distribution; the latter which might itself have a mean that is subject to uncertainty is then averaged over a second-level distribution of that mean. The process may need to be continued, in principle, until the deepest-level distribution has a mean and other statistical parameters that are truly deterministic. The parameter averaging lead to an unconditional pdf which is stationary in the smeared parameters. The minimum window size required for accurate estimation of these parameters increase with the number of levels of averaging as the complexity of the unconditional pdf tends to rise rapidly with each additional level.

At the deepest level, the a-priori information is described with a process stationary in mean (or parameters smeared other than the mean). Among the most used a-priori scene models are the Markov Random fields which are expressed in term of Gibbs Random fields under the local stationarity condition [22]. For accurate estimation of the pdf parameters of such process, large neighbour in which the process is stationary, are required. Segmentation and multi-resolution techniques were used for example in [1], [28] to form an image with separate entities in which the process is stationary. If this not done properly, unrealistic behaviour might be introduced in the filtered image.

V. Speckle filtering of stationary in increment scenes

A. Adaptive filtering

Many digital filters were developed in the field of communication theory to reduce the transmission channel noise which was generally assumed to be white and additive noise. Some of them were adapted to SAR images to filter the multiplicative speckle noise under the adaptive form which is shown to be suitable for stationary in increment signals. The most well know are based on the Minimum Mean Square Error (MMSE) [4], [12], [11], or the Bayesian [11], [16], [1] techniques. These filters which were originally derived for stationary signals are adapted to slowly varying nonstationary signals. The filters parameters are performed within a moving window in which signals can be assumed to be stationary and ergodic. The filter output is a spatially varying (as a function of the processing window position) scalar (or a vector) which corresponds to an estimate of the nonstationary scene function.

In contrast to speckle filters based on the multiplicative model, the filters based on the product (or the multiply stochastic) model requires a priori models at each level of averaging. Speckle filtering is mainly Bayesian model fitting which optimizes the Maximum a posteriori (MAP) criteria [11], [16], [1]. However, speckle filtering under the multiply stochastic model (like for any inverse problem method) is very sensitive to the assumed a-priori models, and unrealistic behaviour might be introduced due to erroneous models [1]. Consequently, unless the a-priori models fit well the reality, methods based on the simple multiplicative model remains more effective, and more attractive as they are expansive in computing time. A promising solution was proposed in [1] which consists in matching various a-priori models to the scene under study at the expanse of large computing time.

B. Multi-resolution adaptive filtering

The filter parameters are calculated using the observed signal statistics within windows (generally of fixed size) in which the signal is locally stationary. Certain parameters like the second order statistics (the covariance function for example) need large windows for an accurate estimation. Filters based on the product model need larger windows than the ones based on the simple multiplicative model of section IV (A and C). Both models have to be applied within a region where the observed and scene signal are locally stationary. As such, the processing window should be of a limited size such as only a "stationary" portion of the illuminated target is covered. Tests of stationarity should be applied on the observed signal to adapt the size and the shape of processing window to signal nonstationarity. As such, the estimation within the selected window of local stationarity leads to accurate and meaningful parameter estimates. This improves significantly the performance of the classical filters which are blindly applied on a moving window of a fixed size. An example is given in [5] concerning the classical box (average) filter. The Hagg filter which is a multi-resolution box filter is much more effective than the classical box filter of a fixed size. One problem with the Hagg filter is that is it only adapted to areas of constant reflectivity (R(t) = constant). The filter, which is not based on a solid method of signal estimation theory (averaging of homogeneous region), is completely ineffective in textured areas (which might be locally stationary but not necessarily locally homogeneous).

VI. Speckle filtering of locally nonstationary scenes

Scene signals might be nonstationary even within a small region. Nonstationarity might be due to the presence of edges, curvilinear features, or point targets. If the scene signal is varying rapidly within the resolution cell, the multiplicative speckle model (and consequently the product model) cannot even be used. Signal variations from one resolution to another within any small neighbourhood makes statistic estimation meaningless. The solution would be to correlate the observed signal with a replica (noise-free ideal signal) which models local scene nonstationarity. Such correlation would improve the signal to the speckle noise ratio, and as such would enhance the nonstationary feature (the source of nonstationarity). The filter might then adapt the shape of the window to the enhanced feature, and as such use a sufficiently large number of independent samples for an accurate estimation of the unspeckled feature signal. Since the underlying scene signal is not known, various replicas might be tested and the one which would enhance the best the scene feature might be selected. Multi-resolution processing remains again the best way to increase the signal to noise ratio of the replica-image correlation. The multi-resolution technique first introduced for SAR images in [25], significantly improves the performance of the ratio edge detector in the presence of small edges, and in areas of low contrast (see [25]).

VII. A protocol for speckle filtering

A. Presentation of the protocol

According to the discussion above, a set of rules (i.e. a protocol) might be set for effective speckle reduction. Filter conception should be done with respect to the protocol presented in Figure 1. This means that any speckle filter should include the following tools:

1. An algorithm which takes into account speckle statistics for speckle reduction of locally stationary areas
2. An algorithm to detect neighbourhood which are not locally stationary,
3. Replicas to match local non-stationarity
4. Algorithm for speckle filtering of locally non-stationary areas as a function of the matched scene replica
5. Multi-resolution algorithms to fit the size and the shape of the neighbour to signal stationarity

B. Applications of the protocol: filters assessment and development

Such a protocol allows one to assess theoretically the performance of any speckle filter. For example, the following filters suffer of a number of weakness:

- The Hagg filter [5] employs a simple box algorithm for speckle filtering of locally stationary areas. As such, texture cannot be preserved,
- The Kuan and Frost filters do not include tools to detect nonstationarity,
- Application of the Bayesians filters with small windows might lead to erroneous filter parameter estimates.
- Filters based on wavelets [2] can only preserve fine structure. They should be equipped with a speckle model based algorithm for an effective speckle filtering within locally stationary areas.

The protocol above was used to develop an MMSE multi-resolution filter. Figures 2, 3, and 4 present the original image (Radarsat fine mode 1-look), and the images filtered with the MMSE filter over 7x7 window, and the multi-resolution MMSE filter. The multi-resolution filter converges to stable values for a 29x29 window size. Obviously, the multi-resolution technique permit better preserving of texture and fine structure with an effective speckle reduction within homogeneous areas.

Conclusion

Speckle filtering of nonstationary scenes can be performed accurately if the scene signal is stationary in increments. Scenes which are not locally stationary should be filtered sepately using a priori replicas of the nonstationary scene feature. The protocol of speckle filtering introduced in this study might be used to assess theoretically the performance of speckle filters. This protocol was used by the author as the basis for the development of a new multi-resolution MMSE filter which is much more effective than the classical MMSE filters. The same multi-resolution technique used here to improve the MMSE filter might be also exploited to improve the performance of many existing filters such as the Frost [4], Lee [13], and MAP Gamma ([16], [19]) filters.

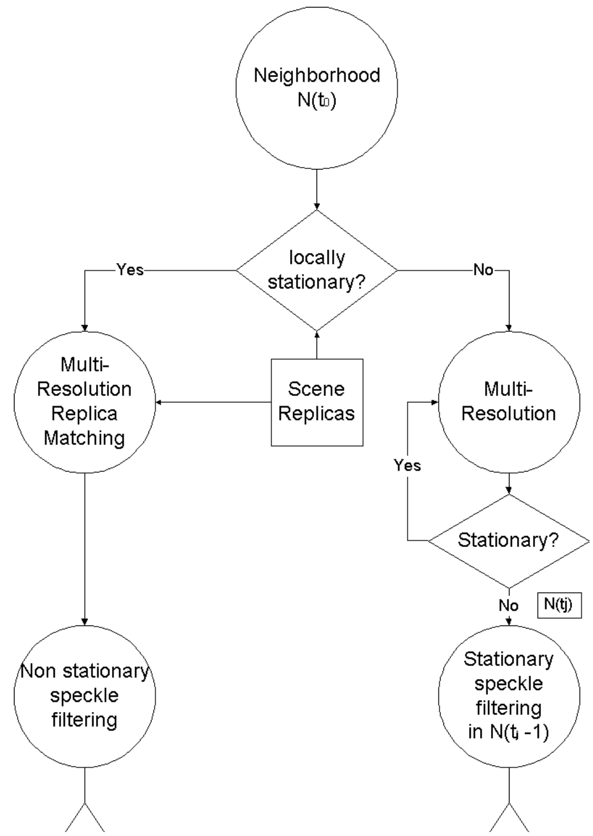

Fig. 1. *Flow chart*

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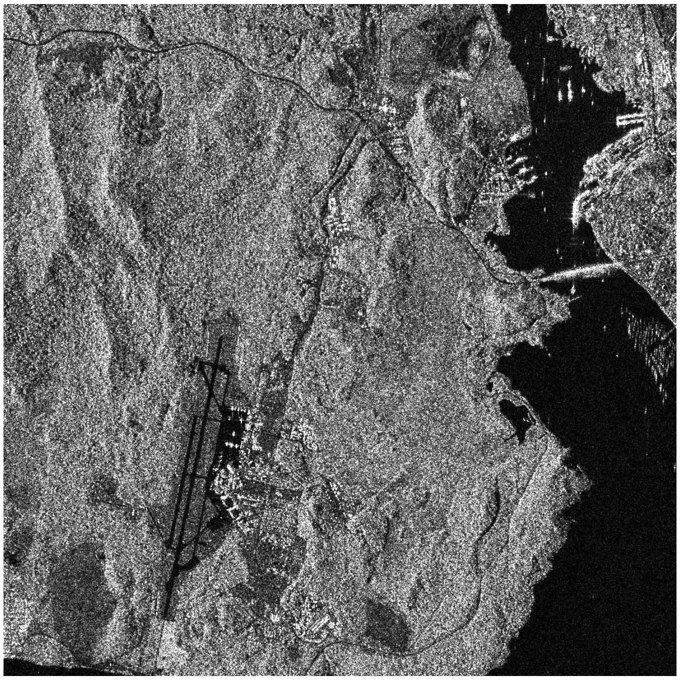

Fig. 2. *Original image*

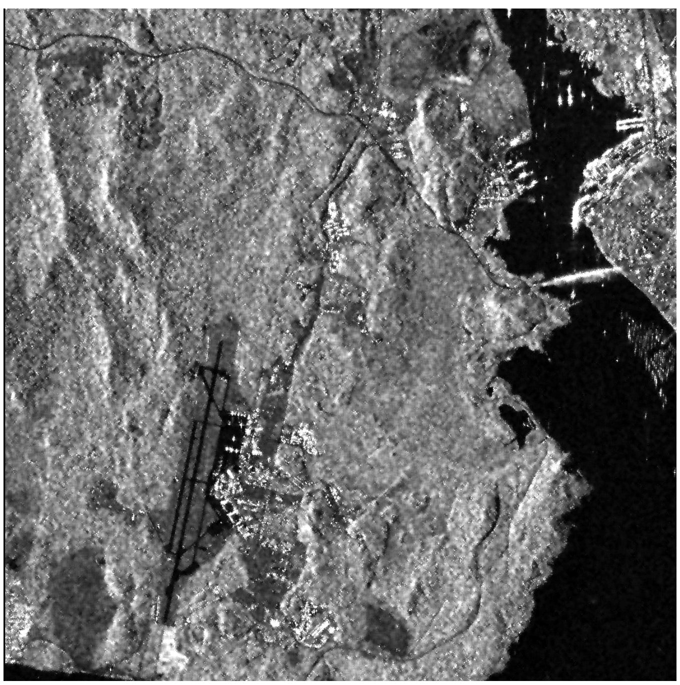

Fig. 3. *MMSE filtered image*

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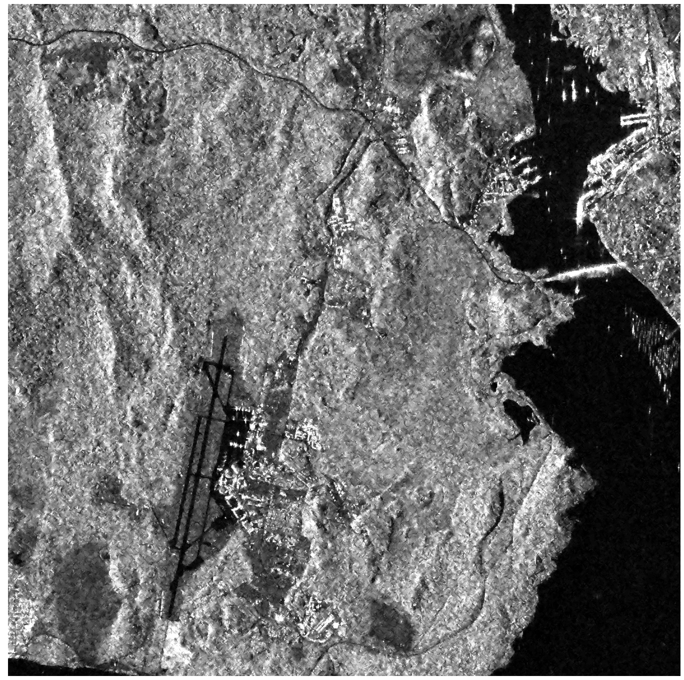

Fig. 4. *Multi-resolution MMSE filtered image*

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