Speckle filtering of stationary and nonstationary scene signals in SAR imagery

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Abstract—**Speckle filtering of nonstationary scenes is studied in the context of estimation theory. It is shown that the problem can be solved separately for stationary in increments scenes, and scenes which are not locally stationary. The speckle multiplicative noise model, the Kuan's nonstationary mean nonstationary variance (NMNV) scene model, and the speckle-scene product model are analysed, and their use for an accurate reconstruction of the underlying scene signal is discussed. A protocol is introduced for speckle filtering of stationary and nonstationary scenes. It is shown that the use of multi-resolution algorithms is crucial for safe reconstruction of the underlying nonstationary radar cross section of the illuminated scene.**

I. Introduction

Speckle filtering of a SAR image 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 [2], [6]. These filters adapt their processing to the nonstationary scene signal by using a spatially moving window of a fixed size. Two families of filters might be distinguished: filters which do not use explicitly the statistical distribution of the underlying scene such as the Lee and Frost filters [2], [6], and filters which use, in addition, an a priori statistical model for the underlying scene signal [5], [9]. The a priori scene model is generally integrated with the speckle multiplicative model to form the named "product model" which is the basis of Bayesian filters. In practice, the two family filters are applied using a moving window of a relatively small size (7x7 window is the mostly used (see [6]) which should provide a satisfactory compromise between speckle reduction and preservation of small structures within a tolerable computing time.

In the following, 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. The speckle multiplicative noise model, the NMNV Kuan scene model, and the product model are analysed in section III. Speckle filtering of locally stationary scenes is studied in section IV. It is shown that the use of a multi-resolution algorithm is crucial for safe reconstruction of the nonstationary reflectivity of the illuminated scene. Finally, speckle filtering of scenes which are not locally stationary is discussed.

II. Speckle filtering in the context of estimation theory

The main objective of speckle filtering is to retrieve the radiometric and spatial scene information "R" from the observed "speckled" SAR measurement "I". This is mainly an estimation problem, and filter development should be performed with respects to certain rules determined by the classical estimation theory. Given one realisation of the stochastic process I(t) observed during a finite interval of time, the estimation of the 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 [4]. 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 [4]), 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.

III. 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) [14], the multiplicative model states that the observed intensity of the pixel located at t=(x,y) is given by [2], [6]: 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 [11], the stationarity assumption on speckle noise is valid 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 partial polarization of the scattered wave [11]) or to the sensor (such as the system impulse response) should remain in the filtered image (for a better characterization of the scene).

B. Scene model for stationary speckle noise

Since speckle is stationary, the observed signal I(t) is nonstationary only if R(t) is not. For an accurate estimation of the observed signal parameters, R(t) should not change significantly within the moving processing window. The scene signal and the observed signals are 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 [5]. It assumes that the scene (and consequently the observed) signals are locally stationary in mean and variance. This model served as the basis of the development of many 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 is the basis of the MAP Bayesian one-level (Gaussian, and Gamma [5], [9]) or multi-level ([1]) filters. The product model is based on a technique developed for characterising nonstationary functions (see [7] 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 [10] to transform a nonstationary correlation function to a stationary function named the spatially averaged correlation function. This method was used in [13] to justify the use of the adaptive coherence estimate for characterisation of nonstationary coherence signals.

In contrast to the previous scene model of (III.B), speckle which is still locally stationary within a resolution cell (i.e. the multiplicative model condition satisfied), is not assumed to be 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 (III.B). This should explain the radiometric bias obtained with the MAP Gamma filter. The bias vanish with increasing number of looks (i.e. larger window size) as shown in [8].

IV. 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 increments signals. The most well know are based on the Minimum Mean Square Error (MMSE) [2], [6], [5], or the Bayesian [5], [9], [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.

B. Why 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 window for an accurate estimation. Filters based on the product model need larger window than the ones based on the simple multiplicative model of section III (A and B). 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 [3] concerning the classical box (average) filter. The multi-resolution box filter adapted to SAR images in [3] is much more effective than the classical box filter of a fixed size. One problem with the multi-resolution box 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).

V. 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 [12], improved a lot the performance of the ratio edge detector in the presence of small edges, and in areas of low contrast (see [12]).

Conclusion

Speckle filtering of nonstationary scenes can be performed accurately if the scene signal is stationary in increments. Scenes which are not locally stationary might be speckle filtered 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 any speckle filter. 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.

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