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Speckle noise reduction in SAS imagery

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Abstract

Synthetic aperture sonar (SAS) is actively used in sea bed imagery. Indeed high resolution images provided by SAS are of great interest, especially for the detection, localization and eventually classification of objects lying on sea bed. SAS images are highly corrupted by a granular multiplicative noise, called speckle noise which reduces spatial and radiometric resolutions. The purpose of this article is to present a new adaptive processing that allows image filtering, for both the additive and multiplicative noise case. This new process is based on the marriage between a multi-resolution transformation and a filtering method. The filtering technique used here is based on the two-dimensional stochastic matched filtering method, which maximizes the signal-to-noise ratio after processing and minimizes mean square error between the signal's approximation and the original one. Results obtained on real SAS data are presented and compared with those obtained using classical processing.

Keywords: SAS images; Speckle; Stochastic matched filter; Multi-resolution analysis; Mallat algorithm

1. Introduction

Over the past few years, synthetic aperture sonar (SAS) has been used in sea bed imagery. Indeed high resolution images provided by SAS are of great interest, especially for the detection, localization and eventually classification of objects lying on sea bed. As with any acoustic imaging system, SAS images are highly corrupted by a granular multiplicative noise, called speckle noise. This reduces spatial and radiometric resolutions. So such a noise can be very disturbing for the interpretation and the automatic analysis of SAS images. For this reason, recently, a great deal of research has been dedicated to reduce this noise and suppress the spacious reflections affecting the images. Some of these speckle reduction techniques try the use of multi-look processing in range, others consider image-domain filters, adaptive filtering or wavelet-domain filtering. The purpose of this article is to present a new adaptive processing that allows image filtering, for both the additive and multiplicative noise case. This processing is based on the two-dimensional stochastic matched filtering method [1–3], which allows to maximize the signal-to-noise ratio after processing. Usually, the largest of the noise frequencies is higher than the largest of the signal

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ones, so classical approaches for noise reduction induce smoothing effects on the resulting image, degrading the signal of interest. For this reason, the stochastic filtering method presented in this paper, only uses the basis functions which minimize the mean square error between the filtered observation signal and the signal of interest. By this way, the proposed processing allows a minimization of the mean square error between the reconstructed signal and the original one and at the same time an improvement of the signal-to-noise ratio, without smoothing effects. Furthermore, the stochastic matched filtering method implies a necessary *a priori* knowledge of the signal and noise autocorrelation functions. Generally, the noise can be assumed stationary. In that condition, it is possible to compute its autocorrelation function. But for the signal, we cannot make such an assumption, so that classically this filtering method is applied using an isotropic average model for the signal autocorrelation function [4]. Taking into account the previous remark, implementation of this filtering technique is not optimal. For this reason, we propose to expand the noise-corrupted signal using a multi-resolution analysis [5], which allows fine details to be separated from larger ones. Various representations are thus extracted from the same image: the scale and the wavelet planes; each of them presents first and second order moments almost invariant by translation. Indeed, wavelet planes present some oriented structures (horizontal, vertical and diagonal), which can be easily described using anisotropic autocorrelation models; while for the scaling plane, corresponding to the low frequencies, an isotropic autocorrelation model can be chosen for the signal. So, through a multi-resolution analysis, four autocorrelation models are used to describe the signal, while only one is required for the space domain approach. So that, such an approach allows a better description of the signal second order statistics; hence the stochastic matched filter assumptions are accurately respected, involving a better restitution of the signal of interest. Experimental results on SAS images are presented andcompared to those obtained using some classical approaches : Lee's filter [6], adaptive mean filter [7], anisotropic diffusion [8], Frost adaptive filter [9], enhanced Frost filter [10,11], Gamma filter [12] and a wavelet domain filter. These techniques are evaluated in terms of speckle level, edge preservation and computational time.

2. The stochastic matched filter

The filtering method presented here is based on an expansion of the observed signal into a weighted sum of known vectors by uncorrelated random variables. The basis vectors are chosen such as each of them contributes to an improvement of the signal-to-noise ratio after processing.

2.1. One-dimensional discrete-time signals: signal-independent additive noise case

Let us consider a noise-corrupted signal $\boldsymbol{Z}$, composed of M successive samples. This one corresponds to the superposition of a signal of interest $\boldsymbol{S}$ with a colored noise $\boldsymbol{N}$. If we consider the signal and noise variances, σ_S^2 and σ_N^2, we have

$$\boldsymbol{Z} = \sigma_S \boldsymbol{S}_0 + \sigma_N \boldsymbol{N}_0, \tag{1}$$

with $E\{\boldsymbol{S}_0^2\} = 1$ and $E\{\boldsymbol{N}_0^2\} = 1$. In the previous relation, reduced signals $\boldsymbol{S}_0$ and $\boldsymbol{N}_0$ are assumed to be independent, stationary and with zero-mean.

It is possible to expand noise-corrupted signal $\boldsymbol{Z}$ into series of the form:

$$\boldsymbol{Z} = \sum_{m=1}^{M} z_m \boldsymbol{\Psi}_m, \tag{2}$$

where $\{z_n\}$ corresponds to a zero mean, uncorrelated random variables sequence and $\{\boldsymbol{\Psi}_m\}$ a M-dimensional deterministic basis.

Classically and using a M-dimensional deterministic basis $\{\boldsymbol{\Phi}_m\}$, random variables z_m can be expressed by the following relation:

$$z_m = \boldsymbol{Z}^{\mathrm{T}} \boldsymbol{\Phi}_m. \tag{3}$$

The determination of these random variables depends on the choice of basis $\{\boldsymbol{\Phi}_m\}$. We will use a basis, which provides the uncorrelation of the random variables, i.e.

$$E\{z_m z_n\} = E\{z_m^2\}\delta_{n,m}, \tag{4}$$

where $\delta_{n,m}$ denotes the Kronecker symbol.

In order to determine basis $\{\boldsymbol{\Phi}_m\}$, let us be interested in the matched filter theory. If we consider a discrete-time, stationary, known input signal $\boldsymbol{s}$, composed of M successive samples, corrupted by an ergodic reduced noise $\boldsymbol{N}_0$, the matched filter theory consists in finding an impulse response $\boldsymbol{\Phi}$, which optimizes the signal-to-noise ratio ρ. Defined as the ratio of the square of signal amplitude to the square of noise amplitude, ρ is