A Proposition of a Bayesian Filter for Despeckling SAR Images Using Conjugate Distribution, Stochastic Distances, and Non-Local Means

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Abstract. *We propose a new Bayesian filter for speckle noise in Synthetic Aperture Radar (SAR) with one-look and quadratic detection. The non-local means filter will be applied over the noisy data modeled by that distribution, using stochastic distances, substituting the original Euclidean distance. We will use non-reference quality measures and we will compare the results with those obtained by state-of-the-art filters.*

Keywords: *SAR, Speckle Noise, Non-Local Means, Stochastic Distances*

1. Introduction

Images obtained by coherent radiation exhibit a type of characteristic noise called speckle. This noise causes difficulty in interpreting the images visually or automatically, and thus it is necessary to reduce it.

From the 1980s onwards, the first filters appeared under the mean squared error criteria, using the spatial neighborhood of the pixels [Lee 1980]. In the 90's, filters were proposed based on the criterion of total variation [Rudin et al. 1992] and wavelets [Donoho and Johnstone 1995]. From the 2000s onwards, the so-called non-local averaging filters emerged, dominating the noise filtering scene [Buades et al. 2005]. More recently, filters based on deep learning have emerged with excellent results. However, such filters need a more solid mathematical formalization and require a large volume of data for their training, in general [Fracastoro et al. 2021].

We divided this paper into three more sections. The following two sections are about contextualization. First, it presents some digital image fundamentals, and then, in the next section, it lays theoretical grounds for understanding the problem and elaborating a solution. The paper finishes with the work proposal section, proposing a new speckle filter based on a Bayesian and computationally efficient formulation.

2. Digital Image Fundamentals

The principal noise sources in digital images arise during image acquisition and transmission. The performance of imaging sensors is affected by various factors, such as environmental conditions during image acquisition and the quality of the sensing elements [Gonzalez and Woods 2017].

2.1. Synthetic Aperture Radar and Speckle Noise

Synthetic Aperture Radar (SAR) is an airborne radar imaging technique for generating high-resolution maps of surfaces. This coherent microwave sensor can penetrate foliage and clouds and can be operated during the day or night because it provides illumination [Berenger et al. 2023].

One of the significant problems in SAR image processing is speckle noise, a common phenomenon in all coherent imaging systems. Random interference between the coherent returns issued by the numerous scatterers on a surface causes this noise. SAR imaging systems can obtain images of large terrain areas at satisfactory resolution and in all weather conditions. Thus, speckle reduction is critical before edge detection and object recognition [Wang et al. 2022].

2.2. Filters

A substantial portion of digital image processing is devoted to image restoration. The image sent from the sender end may differ from the receiving end. When obtaining an image, degradations may occur, and image restoration aims to remove or reduce these.

Filtering refers to accepting or rejecting specific frequency components. For example, a filter that passes low frequencies is called a lowpass filter. The net effect produced by a lowpass filter is to blur (smooth) an image [Gonzalez and Woods 2017].

Additive and multiplicative noise filters, Wiener filters, and adaptive filters are filters that work locally. Non-local means BM3D and PPB filters are currently the filters that instigate researchers focusing on image restoration. They use them to create new versions inspired by the principle of similarity between patches.

3. Theoretical Grounds

3.1. Probability Density Functions and Distributions

Image Restoration includes processes that attempt to remove degradations and restore the original image. Restoration techniques focus on modeling degradation and using the inverse process to recover the original image.

The spatial noise descriptor with which we shall be concerned is the statistical behavior of the intensity values in the noise component of the model. These may be considered random variables characterized by a probability density function (PDF) [Gonzalez and Woods 2017].

Since speckle corrupts the signal in a multiplicative manner and in the amplitude and intensity formats it is non-Gaussian, images suffering from speckle noise should not be treated with the usual additive-noise derived tools.

The multiplicative model is a common framework used to explain the statistical behavior of data obtained with coherent illumination. It assumes that the observations within this kind of image are the outcome of the product of two independent random variables: one modeling the terrain backscatter and the other modeling the speckle noise.

We derived several proper distributions for modeling and analyzing SAR images within the multiplicative model, including the Gama, K, and G0 distributions. These distributions apply to various degrees of heterogeneity and standard image formats [Frery et al. 1997].

3.2. Non-local Means Algorithm for Image Denoising

Many filters developed in the Image Processing literature have a feature in common: they work only locally. That is, a central pixel in a neighborhood of $m \times n$ pixels will have its new value computed and replaced based on the values of all pixels within that spatial neighborhood [Valek and Sekanina 2022].

The NL-means algorithm tries to take advantage of any natural image's high degree of redundancy. The primary and original idea of the algorithm is that the estimate of a noiseless pixel is the weighted average value of all pixels in the image, such that their neighborhoods are similar to the neighborhood of the pixel to be estimated. By this, every small window in a natural image has many similar windows in the same image. The NL-means algorithm uses the Euclidean distance between the grayscale neighborhoods of a pixel to calculate the filter coefficients and their similarities [Buades et al. 2005].

3.3. Stochastic Distances

Stochastic distances are metrics that allow us to measure the "distance" between two probability distributions. Assessing distances between samples is an important step in image analysis as they provide grounds of the separability and, therefore, of the performance of classification procedures. [Wu et al. 2022].

Eight stochastic distances that can be used in statistical tests for contrast identification in speckled data are: Kullback–Leibler, Hellinger, Bhattacharyya, Rényi, Jensen-Shannon, arithmetic–geometric, triangular and harmonic-mean [Nascimento et al. 2010].

4. Work Proposal

We propose using a new filter for speckle noise based on a Bayesian formulation and computationally efficient. It also incorporates the notions of stochastic distances, replacing the Euclidean distance of the original formulation of the non-local filter.

Access to the original noisy image will give us preliminary access to the backscatter by simple filters. The Gamma distribution will model the preliminarily estimated backscatter.

Estimating Gamma parameters depends on two parameters, and one is unitary, corresponding to the number of looks. We will use the original data and assume that they obey the exponential distribution of the speckle (likelihood function in Bayes' rule).

Here lies the approximation of the model: we do not take the backscatter in modeling the noisy image at this point due to the need to have a computationally tractable Bayesian model. With the Gamma a priori distribution, the exponential likelihood function, and the conjugation property, we obtain the Gamma a posteriori distribution by Bayes' rule, which will represent the noisy data.

Estimating the single Gamma parameter involves the original Gamma parameter, the number of observations in the non-local mean filter window, and the sum of the observations in this window. With these parameters estimated, we can now filter the noisy data by the non-local mean filter using the stochastic distances for the Gamma distribution.

We can calculate the Gamma distribution using the stochastic Kullback-Leibler, Rényi, Hellinger, and Bhattacharyya distances. The algorithm calculates the distance between the central patch, which contains the pixel to be filtered, and one of the patches in the search area. This distance depends on two parameters, one from the center patch and one from the search area patch.

The next step is to evaluate the filtering. As we do not have a noise-free image, we must use evaluation criteria without reference, such as the Equivalent Number of Looks (ENL) and Ratio between Noisy and Filtered Images. We will compare the results with state-of-the-art filters and present conclusions and suggestions for future work.

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