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Speckle reduction with adaptive stack filters

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ABSTRACT

Stack filters are a special case of non-linear filters. They have a good performance for filtering images with different types of noise while preserving edges and details. A stack filter decomposes an input image into stacks of binary images according to a set of thresholds. Each binary image is then filtered by a Boolean function, which characterizes the filter. Adaptive stack filters can be computed by training using a prototype (ideal) image and its corrupted version, leading to optimized filters with respect to a loss function. In this work we propose the use of training with selected samples for the estimation of the optimal Boolean function. We study the performance of adaptive stack filters when they are applied to speckled imagery, in particular to Synthetic Aperture Radar (SAR) images. This is done by evaluating the quality of the filtered images through the use of suitable image quality indexes and by measuring the classification accuracy of the resulting images. We used SAR images as input, since they are affected by speckle noise that makes classification a difficult task.

1. Introduction

SAR images are generated by a coherent illumination system and are affected by the coherent interference of the signal from the terrain (Oliver and Quegan, 1998). This interference causes fluctuations of the detected intensity which varies from pixel to pixel, an effect called speckle noise, that also appears in ultrasound-B, laser and sonar imagery.

Speckle noise, unlike noise in optical images, is neither Gaussian nor additive; it follows other distributions and is multiplicative. Classical techniques, therefore, lead to suboptimal results when applied to this kind of imagery. Among the authors that have studied the problem of adapting classical image processing methods to SAR data, Lee (1981) provides a good starting point.

The physics of image formation leads to the following model: the observed data can be described by the random field Z, defined as the product of two independent random fields: X, the backscatter, and Y, the speckle noise.

The backscatter is a physical magnitude that depends on the geometry and water content of the surface being imaged, as well as on the angle of incidence, frequency and polarization of the electromagnetic radiation emitted by the radar. It is the main source of information sought in SAR data.

Speckle has a major impact on the accuracy of classification procedures (Mejail et al., 2003; Capstick and Harris, 2001), since it introduces a low signal-to-noise ratio. The effectiveness of techniques for reducing speckle can be measured, among other quantities (see Moschetti et al., 2006, for instance), through the accuracy of simple classification methods. The most widespread statistical classification technique is Gaussian maximum likelihood.

Different statistical distributions have been proposed in the literature for describing speckled data. Gao (2010) presents a comprehensive and updated survey of univariate distributions able to describe speckled data. In this work, since we are dealing with intensity format, we use the Gamma distribution, denoted by Γ, for the speckle, and the reciprocal of Gamma distribution, denoted by Γ^{-1}, for the backscatter. These assumptions, and the independence between the fields, result in the intensity $\mathcal{G}^0$ law for the return (Frery et al., 1997; Mejail et al., 2003). This family of distributions is indexed by three parameters: roughness α, scale γ, and the number of looks L, and it has been validated as an universal model for several types of targets. Intensity data is obtained by summing the squared real and imaginary parts of the complex return; Vasconcellos et al. (2005) discuss properties of this type of speckled data.

Stack filters are a special case of non-linear filters. They have good performance for improving images with different types of noise while preserving edges and details. Various authors have studied these filters, and many methods have been developed for their construction and application (Prasad, 2005; Shi et al., 2005).

These filters decompose the input image, by thresholds, in binary slices forming a stack of data. Each binary image is then filtered using a Boolean function evaluated on a sliding window. The

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resulting image is obtained summing up all the filtered binary images. The application of stack filters to speckled data was studied by Buemi et al. (2007, 2011).

The main drawback of using stack filters is the need to compute the Boolean functions that satisfy a certain criterion. Direct computation on the set of all Boolean functions is unfeasible, and promising techniques rely on a learning procedure: the use of a pair of images, namely the ideal and corrupted one, and of a loss function. The Boolean functions are sought to provide the best estimator of the former using the latter as input. The stack filter design method used in this work is based on an algorithm proposed by Yoo et al. (1999). The drawback of this line of action is the need of a pure, noiseless image.

Finn et al. (2011) provide a comprehensive and updated review of the literature on speckle filters, with a view towards echocardiographic imagery. They propose a categorization, within which our proposal should be included in the "SAR" category.

We propose the use of user-provided information. The user selects as many regions of interest as desired, and after a descriptive and quantitative analysis of the data, he/she provides an "ideal" value for each region. The Boolean functions are then sought to provide an estimator of such values in the corresponding areas. This approach reduces the computational effort of building the Boolean functions and, at the same time, gives the option of providing a noiseless complete image or specifying "ideal" values in regions chosen by the user.

We study the application of this type of filter to SAR images, assessing its performance by evaluating the quality of the filtered images through the use of objective image quality indexes like the universal image quality index and the correlation measure index and by measuring the classification accuracy of the resulting images using maximum likelihood Gaussian classification.

The structure of this paper is as follows. Section 2 summarizes the $\mathcal{G}^0$ model for speckled data. Section 3 reviews stack filters, and describes the filter design method used in this work. In Section 4 we discuss the results of filtering through image quality assessment and classification performance. Finally, in Section 5 we present the conclusions.

2. The multiplicative model

Following Moschetti et al. (2006), we will only present the univariate intensity case. Other formats (amplitude and complex) are treated in detail in Frery et al. (1997).

The intensity $\mathcal{G}^0$ distribution that describes speckled return Z is characterized by the following density:

$$f(z) = \frac{n^n \Gamma(n-\alpha)}{\gamma^{\alpha}\Gamma(n)\Gamma(-\alpha)} \frac{z^{n-1}}{(\gamma + nz)^{n-\alpha}},$$

where $-\alpha, \gamma, z > 0$, $n \geqslant 1$. This situation is denoted $Z \sim \mathcal{G}^0(\alpha, \gamma, n)$.

The α parameter describes the image roughness or texture. It adopts negative values, varying from $-\infty$ to 0. If α is near 0, then the image data are extremely rough (for example: urban areas), and if α is far from the origin then the data correspond to a smooth region (for example: pasture areas). The values for forests lay in-between.

The r-th order moment of a $\mathcal{G}^0(\alpha, \gamma, n)$-distributed random variable is given by

$$\mathrm{E}(Z^r) = \left(\frac{\gamma}{n}\right)^r \frac{\Gamma(-\alpha - r)\Gamma(n + r)}{\Gamma(-\alpha)\Gamma(n)}, \tag{1}$$

if $-n > \alpha$ and infinite if otherwise.

Many filters have been proposed in the literature for reducing speckle noise, among them the ones by Lee (1986), Kuan et al. (1987), and Frost et al. (1982). These filters will be applied to speckled data, along with the filter proposed in this work. For quality performance the comparison will be done between the results of applying the stack filter and the Lee filter, since the latter is considered one of the touchstones for speckle reduction. Classification performance will be assessed by classifying data filtered with the Lee, Frost and stack filters using Gaussian maximum likelihood. The two first filters can be considered classical choices in the area.

3. Stack filters

This section is dedicated to a brief synthesis of stack filter definitions and design. For more details on this subject, the reader is referred to the works by Astola and Kuosmanen (1997), Lin and Kim (1994), and Yoo et al. (1999).

Consider images of the form $X : S \to \{0, \ldots, M\}$, with S the support and $\{0, \ldots, M\}$ the set of admissible values. The threshold is the set of operators $T^m : \{0, \ldots, M\} \to \{0, 1\}$ given by

$$T^m(x) = \begin{cases} 1 & \text{if } x \geqslant m, \\ 0 & \text{if } x < m. \end{cases}$$

We will use the notation $X^m = T^m(x)$. According to this definition, the value of a non-negative integer number $x \in \{0, \ldots, M\}$ can be reconstructed making the summation of its thresholded values between 0 and M.

In the following, we show an example of the threshold decomposition of an unidimensional signal. Let $X = [2, 1, 3, 2, 3]$ be a signal. Its decomposition is given by: $X^1 = [1, 1, 1, 1, 1]$, $X^2 = [1, 0, 1, 1, 1]$, $X^3 = [0, 0, 1, 0, 1]$.

Let $X = (x_0, \ldots, x_{n-1})$ and $Y = (y_0, \ldots, y_{n-1})$ be binary vectors of length n. Define an order relation given by $X \leqslant Y$ if and only if $x_i \leqslant y_i$ holds true for every i. This relation is reflexive, anti-symmetric and transitive, generating therefore a partial ordering on the set of binary vectors of fixed length.

A Boolean function $f : \{0, 1\}^n \to \{0, 1\}$, where n is the length of the input vectors, has the stacking property if and only if

$$\forall X, Y \in \{0, 1\}^n, \quad X \leqslant Y \Rightarrow f(X) \leqslant f(Y).$$

We say that f is a positive Boolean function if and only if it can be written by means of an expression that contains only non-complemented input variables. That is,

$$f(x_1, x_2, \ldots, x_n) = \bigvee_{i=1}^{K} \bigwedge_{j \in P_i} x_j, \tag{2}$$

where n is the number of arguments of the function, K is the number of terms of the expression and P_i is a subset of the interval $\{1, \ldots, N\}$, '$\vee$' and '$\wedge$' denote, respectively, the AND and OR Boolean operators. It is possible to proof that this type of functions has the stacking property.

A stack filter is defined by the function $S_f : \{0, \ldots, M\}^n \to \{0, \ldots, M\}$, corresponding to the Positive Boolean function $f(x_1, x_2, \ldots, x_n)$ expressed in the form given in Eq. (2). The function S_f can be expressed by means of a summation:

$$S_f(X) = \sum_{m=1}^{M} f(T^m(X)).$$

In this work we applied the stack filter generated with the fast algorithm described in Lin et al. (1990), Lin and Kim (1994), and Yoo et al. (1999).

Stack filters are built by a training process that generates a positive Boolean function that preserves the stacking property. Originally, this training is performed providing two complete images on S, one degraded and one noiseless. The algorithm seeks the operator that best estimates the later using the former as input, with respect to a loss function.