AMPLITUDE BASED INSAR STACK MULTI-LOOKING: PERFORMANCE AND APPLICATIONS

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ABSTRACT

Efficient estimation of the interferometric phase and complex correlation is fundamental for the full exploitation of SAR Interferometry capabilities [1]. Particularly when combining interferometric measures arising both from distributed and concentrated point targets, the interferometric phase has to be correctly extracted in order to preserve its physical meaning and respect the homogeneity hypothesis that we assume when performing a coherent averaging [2]. Recently, an amplitude-based algorithm for the adaptive multilooking of InSAR stacks was proposed [3],[4] where it was shown that a comparison of the backscatter amplitude statistics is a suitable way to adaptively group and average the pixels in order to preserve the phase signatures of natural structures in the observed area.

***Index Terms*—Synthetic Aperture Radar (SAR), interferometry, radar backscatter statistics, coherence estimation, adaptive multilooking**

1. INTRODUCTION

The amplitudes of the complex returns have been proven to be a suitable measure for distinguishing between different areas inside a SAR image [5], thus they can also be used to select a suitable set of pixels over which to average. The concept is to average a given pixel only with neighbors that present similar scattering properties. In this paper different methods to compare amplitude statistics will be presented, compared through simulations and applied to real data. Based on this, recommendations are made concerning which method to use in practice [6]. Finally the physical meaning of the results and the possible applications will be discussed.

2. INTERFEROGRAMS MULTILOOKING

Suppose we have a stack of M complex SAR images co-registered to sub-pixel accuracy and calibrated for each resolution cell p. For each pixel we wish to determine which of the surrounding pixels present a similar statistical behavior. This is possible by noting that for each pixel we can extract M realizations of the process that generated the pixel amplitudes by sampling the stack temporally, naturally assuming that the process can be considered stationary over time. This set of M observations can then be used in order to check the degree of similarity between pixels. Statistically similar pixels can then be averaged together [2].

3. PIXEL CLUSTERING AND PERFORMANCE

Determining whether random processes follow the same distribution is a common problem in statistics, where it is usually referred to as goodness-of-fit testing, and many methods have been developed. In this paper different methods will be tested through simulations and the results compared. The problem is generally defined in a hypothesis testing framework as a test of the null hypothesis, H_0: $F_p = F_q$, that the two distributions F_p and F_q are equal, versus the alternative, H_1: $F_p \neq F_q$, that they are not. For the specific problem of adaptive multi-looking we have selected four typical goodness-of-fit testing criteria for discriminating between the different amplitude distributions: the Kullback-Leibler

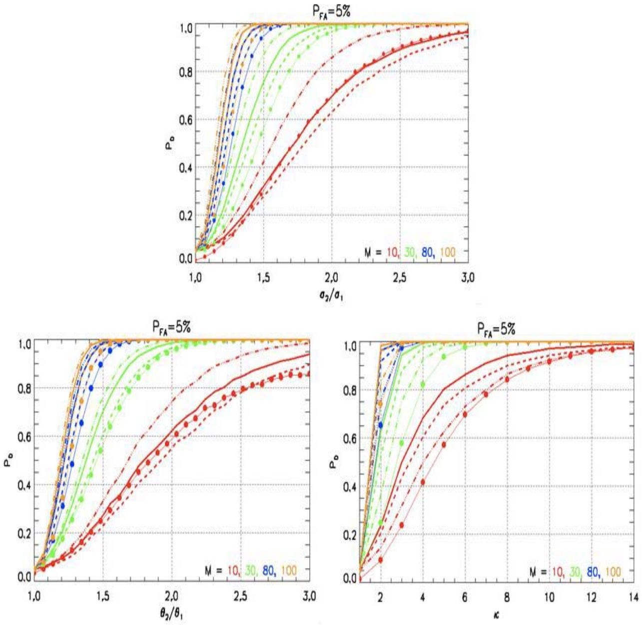

Figure 1. Detection rates for the Kullback-Leibler Divergence (dotted) , Kolmogorov-Smirnov (dashed), Anderson-Darling (solid) and GLRT (dashed/dot). The three cases are respectively, the Rayleigh-distributed case, the K-distributed case varying the scale and the K-distributed case varying the shape. The colors indicate the number of samples M.

divergence [9], the Kolmogorov-Smirnov test [7], the Anderson-Darling test [8] and the GLRT (Generalized Likelihood Ratio Test) [7]. The stack size, M, will clearly play an important role in how well pixels can be classified since the power of the tests increases with sample size. Hence, in the following performance analysis the impact of M is always considered. For all simulations the test thresholds were set to maintain a false alarm rate of $P_{\{FA\}}$= 5 % under the null hypothesis and the power of the test, P_D, or the probability of correctly deciding that the datasets follow different distributions, was plotted as certain distributional parameters were varied. Finally, the number of Monte Carlo simulations used to evaluate the performance was always 10000. Two different amplitudes distributions scenarios have been taken in consideration, the Rayleigh distribution varying the scaling factor σ and the so called K-distribution, [11],[12] varying the scaling factor θ and the shaping factor k Figure 1 [10], [13].

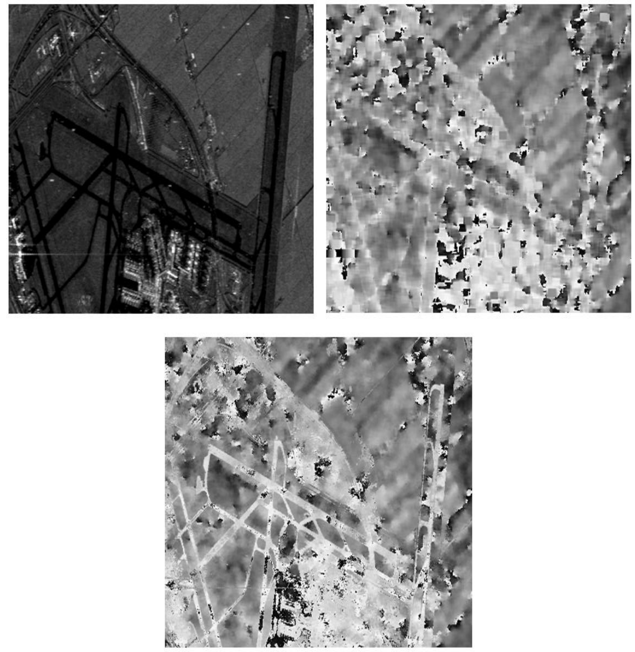

Figure 2. Comparison between the incoherent mean (upper left) and the multi-looked interferometric phase obtained using an 8 x 25 boxcar kernel (upper right) and a 200 look adaptive kernel (below). The interferogram is an ERS 1-2 interferogram with a temporal separation of 35 days and a normal baseline of 107 meters

3.1. Clustering Algorithm

According to the results achieved by the simulation we used the Anderson-Darling test as the kernel for the clustering algorithm [6]. The program proceeds sequentially analyzing the pixels and assigning them to the most similar neighboring class or generating a new class in case they do not fulfill the similarity requirements of the test, as shown in Figure 3. As the number of samples in a class increase, the test will be able to rely on a bigger subset of samples improving the resolution capabilities of the whole algorithm. An example of the results is shown in Figure 5.

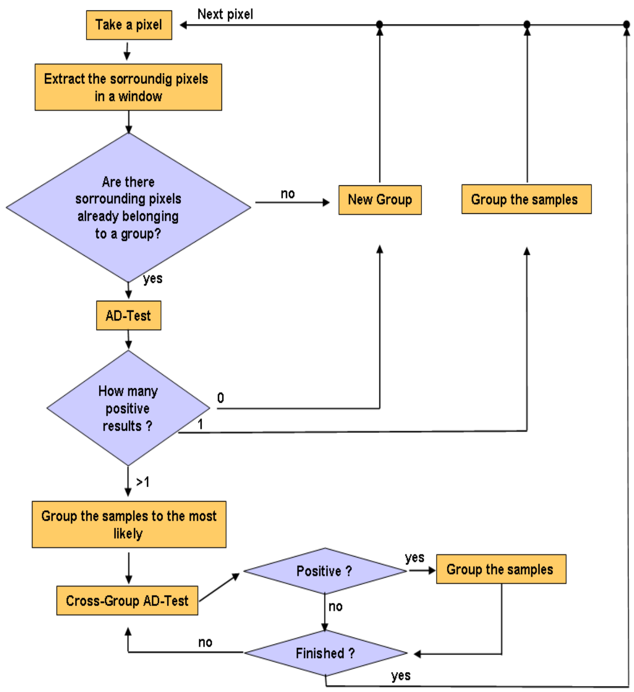

Figure 3. Flow chart diagram of the clustering algorithm above mentioned

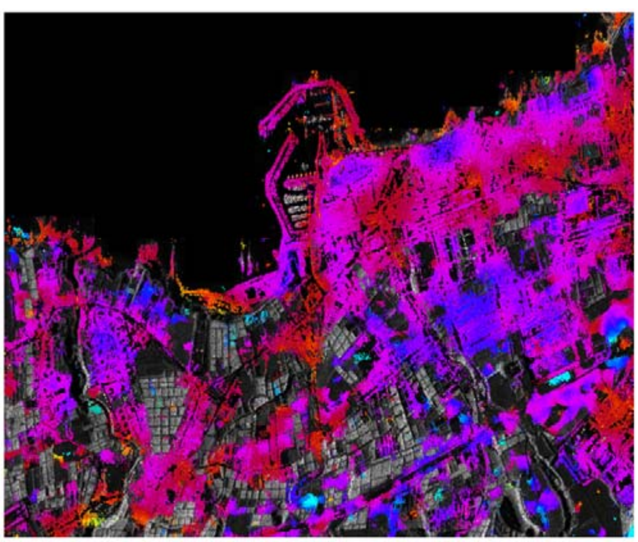

Figure 4. TerraSAR-X Stripmap image overlaid in the coherent areas with the relative adaptive multi-looked interferometric phase.

4. RESULTS AND DISCUSSION

As expected, the adaptive algorithm is able to follow the features of the scene as soon as the contrast is sufficient. Therefore it is possible to obtain a very accurate clustering of the pixels in the area of interest Figure 4 and consequently an optimal estimation of the interferometric phase with only a small loss in resolution compared to a standard boxcar average Figure 2.

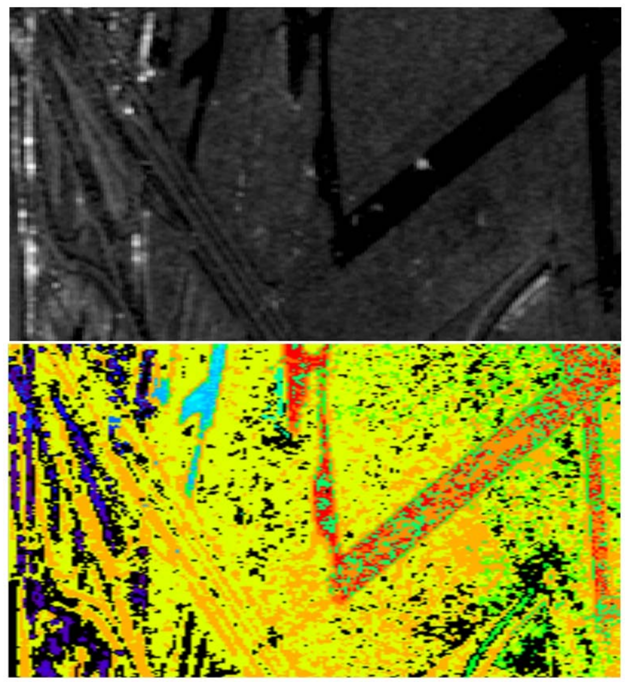

Figure 5. Example of pixel clustering compared with the incoherent mean image. The colors indicate different pixel groups identified by the algorithm.

From the simulations and experiments with InSAR stacks the following conclusions can be drawn:

- Amplitudes statistics are a good indicator for distinguishing between different scattering phenomena in order to preserve the phase signature of natural structures.

- Nonparametric methods are recommended when it is not possible to make assumptions about the statistical properties of the amplitudes. Of the three nonparametric tests, Anderson-Darling was the most powerful. In comparison to the parametric GLRT, it was also more powerful at detecting changes in the shape of a distribution. However, within scale families and especially with small stack sizes, the GLRT was significantly more powerful.
- Different backscatter processes possess different interferometric phases that, even in the case of very low power, nevertheless contain good phase information which can be accurately recovered after sufficient averaging over homogeneous pixels. This points more to a deterministic rather than a stochastic relationship between the backscatter amplitude distribution and the location of the phase center within a resolution cell for distributed scattering processes in SAR, i.e. the phase centers of resolution cells over homogeneous regions are the same.

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