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Object detection in SAR image based on bandlet transform ☆

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ABSTRACT

Object detection in SAR images is a challenging task as these images are inherently affected with speckle noise. This paper presents a novel algorithm based on bandlet transform for object detection in Synthetic Aperture Radar (SAR) images. Here first a bandlet based despeckling scheme is employed on the input SAR image and then a constant false alarm rate (CFAR) detector is used for object detection. The input image is first decomposed using Bandlet transform and the bandlet coefficients so obtained are modified using soft thresholding rule on all sub bands, except for low frequency sub band. The optimum thresholds for each sub bands are computed using generalized cross-validation (GCV) technique which doesn't require the information on noise variance of the input image. The method takes advantage of the geometrical features of bandlet transform for retaining the edges and boundaries of the objects present in SAR images while removing the speckle effectively. Thus CFAR detection on despeckled image can effectively find an optimum threshold for object detection to maintain a constant false alarm rate. The proposed Bandlet transform based scheme surpasses the traditional despeckling and object detection schemes in wavelet domain, in terms of numerical and visual quality.

1. Introduction

Synthetic Aperture Radar (SAR) based remote sensing system is used to obtain high resolution images. The prime advantage of SAR imaging is its capability to provide images on all weather conditions, unaffected through clouds. Here the area to be imaged is illuminated using radio frequency signals and the images of the area are produced using the amplitude and phase information of the radiation which is reflected back. SAR imaging has wide variety of applications such as object detection and identification, crop production forecasting, glacier monitoring, sea ice monitoring, forest fire monitoring, urban growth modeling, disaster monitoring etc. Object detection and identification has many significant military and civil applications such as detection of ships on sea, tanks in land, crashed aircraft etc. The manual interpretation of SAR images for object detection is a difficult task which can lead to large errors. Many attempts have been made in the past decades to develop automatic algorithms for this purpose. The constant false alarm rate (CFAR) algorithm is the most popular algorithm that has been adopted as a first step in many SAR automatic target recognition systems [1]. In CFAR detectors the clutter distribution is always locally estimated so that the decision threshold can be adaptively determined according to a given probability of false alarms. Many of the CFAR detectors are based on the local statistics of the background clutter [1–4]. The most popular object detection algorithms based on CFAR detectors are cell-averaging CFAR (CA-CFAR) detector [5], the two-parameter CFAR (TP-CFAR) detector [6], the order-statistic CFAR detector [7], etc. These basic CFAR detectors work well in situations where the speckle noise in SAR images is less. However most of these systems cannot give satisfactory results due to the presence of speckle noise in SAR images. Speckle noise is generated in SAR images due to the coherent imaging process wherein the reflected wave from the target is a mixture of contributions from various independent scattering points. The interference of these dephased but coherent waves results in a disturbing pattern in the image called "speckle". The level of speckle increases as the power of the signal increases. Hence, speckle is considered as a multiplicative noise with a standard deviation equal to the reflectivity value.

The speckle noise makes it difficult to analyze and interpret SAR images. This makes SAR despeckling a mandatory pre processing step in SAR image processing. Traditionally many schemes are available for despeckling. These are broadly classified as spatial and transform domain filtering schemes. The spatial filtering

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schemes like Lee filter [8], Kaun filter [9], Frost filter [10], etc. can effectively despeckle the homogenous areas, whereas these schemes blur the heterogeneous areas in the image. The transform domain schemes are mainly based on 2-D wavelet transform (2D WT) [11–13]. It has several limitations like shift-sensitivity and poor directional selectivity. A small shift in the input signal can cause significant variations in the distribution of the energy between the WT coefficients even at different scales which results in shift sensitivity. This makes WT unsuitable for despeckling applications. Also 2D WT has poor directional selectivity, as it has only subbands in three directions namely diagonal, vertical and horizontal. Thus it can only be employed to approximate point singularities and not line singularities like boundaries or edges in images. The 2-D WT cannot retrieve the fine details of the texture in images as it carries out an isotropic regularization only. In images the geometric regularity of the edges is anisotropic in nature. Even though the image edges are discontinuous over a contour, it is differential along the direction which is parallel to the tangent of the edge. Therefore a more effective transform with spatially anisotropic basis functions and multi-directional vanishing moments is required for real-world images to properly capture the geometrical coherence of edges and contours present in them. Towards this end many directional, multi-scale transforms were developed over the past decade for image representations. Most notable among them are the curvelets [14], contourlets [15], wedgelets [16], directionlets [17], etc. SAR despeckling schemes based on these transforms are available in literature. Some of the best schemes are reported in [18–21]. However, on comparison with the standard discrete WT, most of these directional transforms have higher computational complexity. They also require over sampling along with non -separable convolution and filter design. Moreover in some of these schemes, the directions of transform are not adaptive to local dominant directions in the images and filtering is not done in discrete domain making it difficult to use them on discrete images. Bandlet Transform (BT) [22–23] is an exception as it can construct elongated orthogonal vectors in the same direction, where the regularity of function is maximum.

Here a novel object detection algorithm for SAR images using bandlet transform is proposed. The SAR image is first despeckled using bandlet transform. A threshold based despeckling scheme is employed here by using a generalized cross-validation (GCV) method [24] to compute the threshold to avoid the requirement of the prior knowledge of the noise variance in the computation. The objects are finally identified from the despeckled image using amplitude based CFAR detector. The proposed scheme is conceptually simple and computationally efficient with very high detection rate.

The rest of the paper is organized as follows. In Section 2, the theoretical concepts of bandlet transform are presented. Section 3 explains the proposed object detection algorithm in bandlet domain. Experimental results with synthetic and real SAR images are presented in Section 4. Finally, conclusions are given in Section 5.

2. Orthogonal bandlets

Bandlet transform [22] is an adaptive wavelet basis transform which uses the anisotropic regularity in images to build orthogonal vectors. These elongated orthogonal vectors are in the same direction, where the regularity of function is maximum. The bandlet transform performs a bandletization and takes advantages of geometric image regularity and thereby remove the redundancy of a warped wavelet transform. The bandlet transform is non orthogonal in nature and the phenomenon of warping introduces boundary artifacts. To overcome these disadvantages, second generation bandlet transform [23] was introduced. It is built over a standard orthogonal wavelet transform and is implemented by applying 1D wavelet transform on reordered 2D wavelet coefficients.

2D wavelet transform built on orthogonal and biorthogonal filter banks is employed in obtaining the bandlet transform. Bandlet transform yields four images which contain the low and high frequency components of the input image. In order to perform bandlet transform, a dyadic square is selected and the input wavelet image is repeatedly split to form four new sub-squares. Each of the sub-squares is then subjected to a geometric flow parameterization along all possible directions. The number of possible directions is around $2n^2$ where n is the width of the sub-squares in number of pixels. The sampling location is projected along the possible directions. For a particular direction d, we obtain a series of 1-D points from which we can get the 1D discrete signal, f_d by sorting the obtained points in the left to right direction. A 1-D discrete wavelet transform is then performed on the signal f_d. The bandlet transform finds the best possible direction which gives the least approximation error for a particular user-defined threshold T. The direction, d which minimizes the Lagrangian cost function $\mathscr{L}(f_d, R)$ is the best direction and it gives the best geometry [25–26]. The Lagrangian cost function is given by,

$$\mathscr{L}(f_d, R) = \|f_d - f_{dR}\|^2 + \lambda T^2 (R_G + R_B) \quad (1)$$

where f_{dR} is the signal retrieved from quantized coefficients obtained as a result of 1-D inverse wavelet transform. The geometric parameter and quantized coefficients are represented by R_G and R_B number of bits respectively. Here λ is Lagrange multiplier, the value of which is chosen as 3/28. The quad tree can be built after obtaining the optimum approximations in all the dyadic squares. The optimum approximation in the dyadic squares is obtained by minimizing the Lagrangian cost function. The algorithm follows a bottom-up approach where the approximations start at the leaves of the quad tree i.e., the smallest dyadic squares and move up the tree by initializing the cumulative Lagrangian of the sub-trees.

3. Object detection using bandlets

The proposed automatic target detection system for SAR images consists of two stages: despeckling and detection. The despeckling

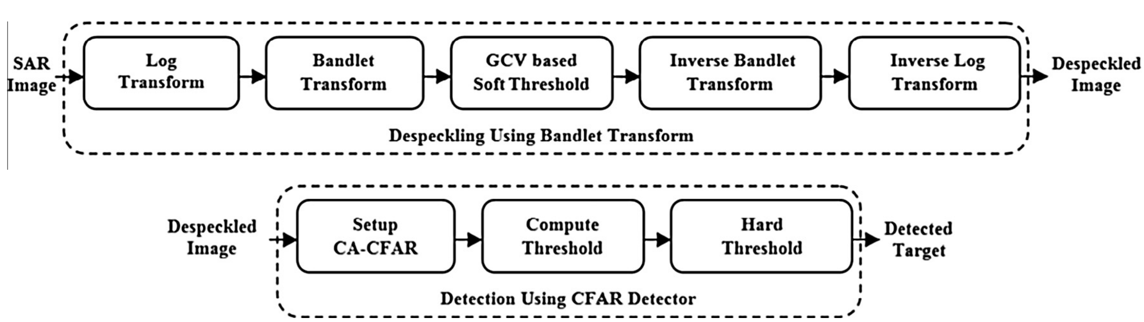

Fig. 1. Automatic target detection system.