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An enhanced approach based on energy loss for multichannel SAR-GMTI systems in heterogeneous environment

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For ground moving target indication (GMTI) in heterogeneous terrains, most detectors could not effectively solve the problem of a high probability of false alarms (PFA) due to the presence of isolated interference with large radar cross section (RCS). To address this issue, we construct a new criterion called as energy loss, which is the energy difference between input and output in the adaptive processing, and develop an enhanced approach based on energy loss for multichannel synthetic aperture radar (SAR)-GMTI systems in heterogeneous environment. In this method, the magnitude-based detection after clutter suppression is first applied to detect potential targets with a relatively low threshold. Then, a complementary detection based on energy loss test is performed to reduce false alarms. To compute the detection thresholds, the statistics of the energy loss test and the overall PFA of the detection approach are analyzed theoretically. Finally, the experimental results on simulations and real data, collected in China's urban area, demonstrate the superiority of the proposed approach compared with state-of-art methods.

1. Introduction

Ground moving target indication (GMTI) in airborne or space-based synthetic aperture radar (SAR) has currently raised much attention due to the extensive applications in traffic monitoring as well as in military surveillance activities [1–7].

Till now, many investigations were carried out to improve the ground moving target detection techniques. Most of them are based on the magnitude test, such as Kelly's generalized likelihood ratio test (GLRT) [8], adaptive matched filter (AMF) [9,10], the imaging adaptive space–time processing (ISTAP) method [11], and a class of two-stage decision schemes [12–14]. These methods proved their effectiveness for GMTI in homogeneous clutter background. However, in heterogeneous environment, these magnitude-based methods may detect false alarms caused by the isolated interference with large radar cross section (RCS). One may expect to raise the threshold for magnitude-based detection to reduce the false alarms, but the probability of detection (Pd) for ground moving targets declines inevitably. For defocused SAR images of heterogeneous terrains, Pd for moving targets decreases even more. In recent years, the problem of SAR image defocussing has been receiving significant research efforts [5], [15–22], [51]. In [15], an iterative compensating method for multiple scattering errors using the estimates of target distribution was proposed to improve the SAR imaging. Based on the scalar form of Maxwell's equation, a general model for radar echoes was derived in the literatures [16–18], and a novel compressive sensing method for general SAR imaging was developed [18]. For the platform motional error compensation, the back projection (BP) algorithms and their improved methods offer a number of advantages over the traditional SAR image formations [19,20]. In addition, in the literatures [21] and [5], the target refocusing approaches was proposed to form well-focused image for high-speed targets. These methods are able to improve the quality of SAR imaging; therefore, the performance of moving target detection in SAR images can be improved. However, these methods could not solve the problem of a high probability of false alarms (PFA) caused by isolated strong interference in heterogeneous background.

Recently, with the development of sensors and imaging techniques, along-track interferometric SAR (ATI-SAR) has been widely studied, and proved to be a valuable tool for GMTI in heterogeneous terrains [23–27]. The interferometric phase detector was investigated by Gierull et al. [23], and the research shows that the interferogram-phase-only detector performs a poor detection performance due to the decorrelation of received signals between two

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channels in GMTI. Then, an improved detection approach was proposed in [24], which employs the displaced phase center antenna (DPCA) test as the first detection, followed with the interferometric phase detector as the second detection. The effectiveness of this two-step detector was validated by the experimental results on the dataset measured during the RADARSAT-2's commissioning phase. In addition, a number of two-stage detectors were discussed in [25–27], which mainly join the magnitude-based test with the transforming of interferometric phase to detect moving targets. However, these methods may be unsuitable for slowly moving target detection within multichannel SAR systems. On one hand the interferometric phase or the transforming of interferometric phase are only performed on the limited sensors (channels); therefore, this cannot make full use of the spatial degrees of freedom (DoF) for multichannel SAR systems [28–30], [52]. On the other hand, due to various nonlinear system errors and clutter internal motions during the signal collection, interferometric phase differences between slowly moving targets and clutter become obscure. In the preceding methods, these real conditions result in the deterioration of the minimum detectable velocity (MDV) in SAR GMTI [23], [31,32].

To address this issue, in this paper, we construct a novel test criterion, called as energy loss, and develop an enhanced approach based on energy loss for multichannel SAR-GMTI systems in heterogeneous environment.

The energy loss in this paper is energy difference between input and output in the adaptive processing. According to the space–time adaptive processing theory in [28] and [30], the energy difference for a moving target is much less than that for clutter, especially for strong clutter. Thus, the energy loss test is able to effectively distinguish moving targets from the background terrains.

In the proposed detection approach, we use the known two-step detection scheme to realize the target detection process. In the first stage, the magnitude-based detection after the clutter suppression is applied to detect the potential targets with a relatively low detection threshold. Then, the radial velocity for each potential target is estimated and its input energy is acquired using the oblique projection approach [33–35]. After that, energy loss test for each potential target is constructed. Of the detected targets in the magnitude-based detection, because most false alarms are caused by strong residual clutter, which has much more energy loss compared with moving targets, the following energy loss detection is able to accurately identify the moving targets, including the slowly moving targets. As a result, targets can be detected as many as possible while most false alarms are removed. In this paper, the statistical characteristics of the energy loss test and the overall PFA of the proposed detection approach are derived; therefore, two detection thresholds can be adaptively computed with the given PFAs. To evaluate the detection performance, experiments on simulations and real dataset are performed, and the experimental results powerfully validate the effectiveness of the proposed method.

The remainder of this paper is organized as follows. Section 2 establishes the signal model of radar receives for multichannel SAR-GMTI systems. In Section 3, the proposed algorithm is introduced and implementing procedures are given. A comprehensive discussion about the achievable detection performance is analyzed in Section 4. Section 5 presents the experimental results, and followed by a detail analysis. Finally, conclusions are drawn in Section 6. Throughout, we denote vectors as lowercase bold letters, matrices as uppercase bold letters, the complex conjugate transpose as a^{H}, and the transpose operator as b^{T}.

2. Mathematical model of received signal

As shown in Fig. 1, the radar platform moves along x axis with a constant velocity of V_a, and the platform trajectory is in the direction of azimuth. The whole antenna is divided into N channels in azimuth. The first channel transmits radar pulses and all the channels separately receive echoes. Assume that these channels are uniformly distributed in a line with an identical space of d.

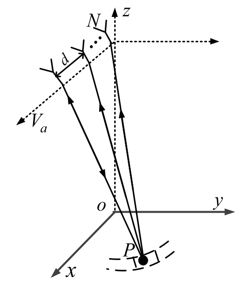

Fig. 1. Along-track multichannel SAR geometry.

In N-channel SAR systems, after the platform's motion compensation, the SAR imaging along the azimuth and range, the precise calibration and coregistration, as well as the necessary terrain interferometric phase compensation [36], N SAR images of the same site are separately acquired by N channels along the platform track. The data vector of N images for a pixel m is denoted by $\mathbf{z}(m) = \left[z_1(m), \quad \ldots, \quad z_N(m)\right]^{\mathrm{T}}$, and thus the signal model can be formulated as:

$$\begin{aligned} &H_0 : \mathbf{z}(m) = \boldsymbol{\sigma}_c(m)\mathbf{a}_c + \mathbf{n}(m) \\ &H_1 : \mathbf{z}(m) = \boldsymbol{\sigma}_s(m)\mathbf{a}_s(v_r) + \boldsymbol{\sigma}_c(m)\mathbf{a}_c + \mathbf{n}(m) \end{aligned} \tag{1}$$

where H_0 denotes the null hypothesis that no target exists, and H_1 denotes the alternative hypothesis that a moving target appears.

$$\mathbf{a}_s(v_r) = \left[1, \exp\left(j2\pi \frac{d}{\lambda}\frac{v_r}{V_a}\right), \ldots, \exp\left(j2\pi \frac{(N-1)d}{\lambda}\frac{v_r}{V_a}\right)\right]^{\mathrm{T}},$$

$\mathbf{a}_c = \left[1, \quad 1, \quad \cdots, \quad 1\right]^{\mathrm{T}} \in \mathbb{C}^{N\times 1}$ and λ represent space steering vector of a moving target with a radial velocity of v_r, space steering vector of clutter, and radar wavelength, respectively. Considering the magnitude fluctuating among N-channel echoes for the same pixel, we denote the complex magnitude of a moving target and clutter as $\boldsymbol{\sigma}_s(m) = diag\left(\sigma_{s1}(m), \quad \cdots, \quad \sigma_{sN}(m)\right)$ and $\boldsymbol{\sigma}_c(m) = diag\left(\sigma_{c1}(m), \quad \cdots, \quad \sigma_{cN}(m)\right)$, respectively. $\mathbf{n}(m) \in \mathbb{C}^{N\times 1}$ represents the noise vector modeled as complex Gaussian distribution.

Following the signal model in (1), the conventional magnitude-based detection is expressed as:

$$T = \mathbf{w}^{\mathrm{H}}\mathbf{z}\mathbf{z}^{\mathrm{H}}\mathbf{w} \underset{H_0}{\overset{H_1}{\gtrless}} \eta \tag{2}$$

where $\mathbf{w}$ is a constant vector, $\|\mathbf{w}\| = 1$, calculated using clutter rejection techniques, such as the adaptive matched filter (AMF) [11], [30], [37,38] and the DPCA techniques [39,40], H denotes the complex conjugate transpose, and η denotes the detection threshold.

In Eq. (2), the magnitude based test T reflects the signal magnitude after the clutter suppression. Because the depth and location of filter notch in the adaptive clutter suppression process are controlled by the clutter covariance matrix (CCM), estimated from training samples, clutter statistical properties affect the clutter suppression result and the magnitude-based detection scheme. In homogeneous Gaussian background, the traditional Sample Covariance Matrix (SCM) is the maximum likelihood estimator (MLE) for CCM [28]. In this case, residual clutter after the clutter suppression approaches to noise level, and targets can be detected accurately from background based on their larger magnitude. However, in heterogeneous background, clutter appears to be non-Gaussian