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# Knowledge-based adaptive detection of radar targets in generalized Pareto clutter

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ABSTRACT

This paper studies adaptive detection of radar targets embedded in generalized Pareto clutter on the condition with the limited secondary data. In order to alleviate the effects of the non-Gaussian characteristic of the clutter, *a-priori* knowledge of the non-Gaussian clutter is considered in the designed detector. More precisely, we consider that the texture of clutter obeys the inverse gamma distribution and the inverse covariance matrix of speckle is a combination of multiple *a-priori* spectral models. Within these considerations, we obtain an adaptive detector based on the generalized likelihood ratio test. Finally, the performance of the proposed detector is evaluated via the Monte-Carlo technique. The experiments results indicate that the proposed detector outperforms the 1S-GLRT detector in limited secondary data scenarios.



## 1. Introduction

The adaptive detection of radar targets in non-Gaussian clutter environment has been extensively researched in recent years. If the detectors are designed for the Gaussian clutter background, occurrence of non-Gaussian clutter would increase the false alarm rate. Therefore, it is necessary to study the non-Gaussian characteristic of clutter and design the detectors which match the clutter's characteristic, in order to obtain satisfactory detection performance. In order to characterize non-Gaussian clutter as precisely as possible, a variety of clutter models are proposed [1–3]. The compound Gaussian clutter model is widely used in clutter statistical model, because it is proved to be effective and practical from the physical mechanism and measured clutter data [4]. Compound Gaussian model can describe the non-Gaussian clutter as the product of a slowly varying positive texture component and a fast varying multivariate complex Gaussian speckle component [5]. As the texture component of clutter follows the gamma distribution, the amplitude of clutter is the K distribution [2]. Weinberg utilized the generalized Pareto distribution to model the power of non-Gaussian clutter, whose texture is the random variable of inverse gamma distribution. Generalized Pareto power distribution is suitable to characterize the heavier clutter than K distribution [3].

Clutter characteristics have significant impact on target detection performance. The detection performance of detectors can be enhanced when the clutter statistical distribution is considered. The optimal detectors are derived in K-distributed clutter environment [6]. Shape-parameter-dependent matched filter (MF) detectors with low computational cost are proposed in K-distributed clutter and the simulated results indicate that they have better detection performance than matched filter (MF) and normalized matched filter (NMF) detectors, and are comparable with the optimal detectors in K-distributed clutter [7]. When the texture follows the inverse Gamma distribution, the relevant detectors of adaptive point-like targets are proposed and the assessment experiments of detection performances show that the proposed detectors perform better than the detectors which do not utilize the knowledge of texture component [8].

In most adaptive detection schemes, the algorithms require the estimate of the clutter covariance matrix from signal-free data (secondary data), which are obtained from range-cells adjacent to the primary data cells. The sample covariance matrix (SCM) estimator [9], the normalized sample covariance matrix (NSCM) estimator [10] and the recursive estimator (RE) [11] are widely used to estimate the covariance matrix. The estimation accuracy of the covariance matrix depends on the number of secondary data and affects the detection performance of adaptive algorithms. Generally, in Gaussian clutter environment, the number of secondary data is required to be more than twice the number of the integrated pulse. In non-Gaussian situation, more secondary data are needed due to the non-Gaussian clutter properties. Meanwhile, it is considered that the primary data and secondary data share the same covariance matrix structure. However, the assumption of homogeneous clutter environment is somewhat idealistic [10] and the

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heterogeneous environment is always encountered [12]. In heterogeneous clutter environment, secondary data are limited to estimate the covariance matrix and this would result in the severe detection performance loss for the adaptive detectors. *A-priori* information of the inverse covariance matrix is considered in order to mitigate the effects of heterogeneity of environment. Recently, multiple *a-priori* spectral models are proposed to model the actual clutter's inverse covariance matrix. In [13], the authors assume that the inverse covariance matrix can be modeled as a linear combination of some available *a-priori* models and experiment result shows that the proposed detectors outperform conventional generalized likelihood ratio test (GLRT) detector and adaptive MF (AMF) detector.

In this paper, we consider the adaptive detection problem of radar targets with the limited secondary data. In order to alleviate the effects of heterogeneous clutter environment, *a-priori* knowledge about clutter is considered. More precisely, we model the texture component of clutter as the random variable which follows the inverse gamma distribution in order to match the real non-Gaussian clutter characteristic. Moreover, the inverse covariance matrix of the speckle component is considered to be a linear combination of some available *a-priori* models in the interest of improving the detection performance in the limited secondary data environment. Within these considerations, we devise a novel adaptive detector based on GLRT.

The paper is organized as follows. In Section 2, the problem formulation is dealt with and the target and clutter models are introduced. In Section 3, the adaptive detector is derived. The detection performances are evaluated in Section 4. Finally, conclusions are mentioned in Section 5.

## 2. Problem formulation

Assume a radar transmits a coherent train of $N$ pulses and the $N$-dimensional complex vector $\mathbf{z}=[z(1),\ldots,z(N)]^T$ denotes the radar returns (also called the primary data), where $(\cdot)^T$ denotes the transpose of the argument. The decision on the existence of a target embedded in compound Gaussian clutter environment can be formulated in terms of the following binary hypotheses test:

$$\begin{cases} H_0: \mathbf{z}=\mathbf{c} \\ H_1: \mathbf{z}=\alpha\mathbf{p}+\mathbf{c} \end{cases} \tag{1}$$

where the null hypothesis $H_0$ means that the complex vector $\mathbf{z}$ is only the echo of clutter and the alternative hypothesis $H_1$ is the target echoes plus clutter situation; $\mathbf{p}=[1,e^{j2\pi f_d},\ldots,e^{j2\pi(N-1)f_d}]^T/\sqrt{N}$ is the normalized steering vector, $f_d$ denotes the normalized target Doppler frequency; $\alpha$ is the unknown deterministic complex amplitude of the target, which accounts for both the target and the channel effects.

The texture component of clutter in each range cell can be regarded as a random constant in a coherent processing interval (CPI) because the coherence length of the texture component is much longer than the coherent processing interval [14]. Consequently, the compound Gaussian model degrades into the spherically invariant random vector (SIRV) model which is widely applied in radar target detection [15]. The clutter vector $\mathbf{c}$ can be interpreted as the product of a real positive random variable and $N$-dimension complex Gaussian circular random vector according to SIRV and so we can get:

$$\mathbf{c}=\sqrt{\tau}\mathbf{u} \tag{2}$$

where texture component $\tau$ is a positive random variable and reflects the power fluctuation. For matching the real clutter characteristic in practical application, the texture component is considered to follow the inverse gamma distribution [8,16]:

$$f(\tau)=\frac{1}{\mu^\lambda\Gamma(\lambda)}\tau^{-(\lambda+1)}\exp\left(-\frac{1}{\mu\tau}\right),\tau>0 \tag{3}$$

where $\lambda$ denotes the shape parameter which represents the non-Gaussianity of clutter and $\mu$ denotes the scale parameter. The speckle component $\mathbf{u}$ is a $N$-dimensional complex Gaussian vector with zero mean and an $N\times N$-dimensional covariance matrix $\mathbf{R}=E(\mathbf{u}\mathbf{u}^H)$, where the diagonal elements of $\mathbf{R}$ are all equal to one. Here, $E(\cdot)$ denotes the statistical expectation operation and $(\cdot)^H$ denotes the conjugate transpose. Accordingly, the conditional covariance matrix of $\mathbf{c}$ for a given $\tau$ is $\mathbf{\Sigma}=E(\mathbf{c}\mathbf{c}^H|\tau)=\tau\mathbf{R}$. Usually, the role of secondary data is to estimate the covariance matrix $\mathbf{R}$ [9]. The more the available secondary data are, the more accurate the estimated covariance matrix is. However, we have to consider this case that the available secondary data may become deficient in practical application. Deficient secondary data means that they cannot provide enough information to obtain an accurate covariance matrix. Naturally, *a-priori* knowledge can be utilized. Therefore, we can design some different models within the known structure to be *a-priori* knowledge. In order to solve the problem that the clutter's heterogeneity leads to a decrease of the usable secondary data, we suppose that inverse covariance matrix of speckle is the linear combination of some available *a-priori* models and belongs to the uncertainty set [13,17–19]

$$A=\left\{\mathbf{M}\succ\mathbf{0}:\mathbf{M}=\frac{1}{K}\sum_{i=0}^{K}t_i\tilde{\mathbf{R}}_i\right\} \tag{4}$$

where $\mathbf{X}\succ\mathbf{0}$ means that the matrix $\mathbf{X}$ is positive definite and the matrix $\mathbf{M}$ is the inverse matrix of covariance matrix $\mathbf{R}$. $\tilde{\mathbf{R}}_i$, $i=1,\ldots,K$, denote the multiple *a-priori* models for the clutter structure, which are available and assumed to be positive definite, *i.e.* $\tilde{\mathbf{R}}_i\succ\mathbf{0}$. In addition, $t_i\in\mathbb{R}$, $i=1,\ldots,K$, are the unknown coefficients.

According to the previous analyses, the conditional probability density function (PDF) of the primary data $\mathbf{z}$ can be written under $H_0$ hypothesis and $H_1$ hypothesis as follows:

$$f(\mathbf{z}|\mathbf{M},\tau;H_0)=\frac{|\mathbf{M}|}{(\tau\pi)^N}\exp\left(-\tau^{-1}\mathbf{z}^H\mathbf{M}\mathbf{z}\right) \tag{5}$$

$$f(\mathbf{z}|\alpha,\tau,\mathbf{M};H_1)=\frac{|\mathbf{M}|}{(\tau\pi)^N}\exp\left(-\tau^{-1}(\mathbf{z}-\alpha\mathbf{p})^H\mathbf{M}(\mathbf{z}-\alpha\mathbf{p})\right) \tag{6}$$

where $|\cdot|$ is the determinant of a matrix.

## 3. Detectors design

In this section, an adaptive detector based on GLRT test is developed for radar targets in generalized Pareto clutter. The aforementioned binary hypothesis test has no an optimum solution due to the existence of the unknown parameters. The GLRT [20] is the suboptimum solution and the GLRT for the problem of interest takes the form of:

$$\frac{\max\limits_{\alpha,\mathbf{M}\in A}\int f(\mathbf{z}|\alpha,\tau,\mathbf{M};H_1)f(\tau)d\tau}{\max\limits_{\mathbf{M}\in A}\int f(\mathbf{z}|\mathbf{M},\tau;H_0)f(\tau)d\tau}\ \underset{H_0}{\overset{H_1}{\gtrless}}\ \gamma_{GLRT} \tag{7}$$

where $\gamma_{GLRT}$ is the detection threshold to be set according to the desired probability of false alarm.

Firstly, we compute the integral of the texture component of clutter in $H_1$ hypothesis according to (3) and (6):

$$\begin{aligned} f(\mathbf{z}|\alpha,\mathbf{M};H_1)&=\int f(\mathbf{z}|\alpha,\tau,\mathbf{M};H_1)f(\tau)d\tau \\ &=\frac{\Gamma(\lambda+N)|\mathbf{M}|\left[(\mathbf{z}-\alpha\mathbf{p})^H\mathbf{M}(\mathbf{z}-\alpha\mathbf{p})+1/\mu\right]^{-(\lambda+N)}}{\pi^N\mu^\lambda\Gamma(\lambda)} \end{aligned} \tag{8}$$