Range Migrating Target Detection in Correlated Compound-Gaussian Clutter

Nikita Petrov, François Le Chevalier, Nikola Bogdanović and Alexander Yarovoy
Microwave Sensing, Signals and Systems (MS3)
Delft University of Technology, the Netherlands
Email: n.petrov@tudelft.nl

***Abstract*—The problem of range-migrating target detection in a compound-Gaussian clutter is studied here. We assume a target to have a range-walk of a few range cells during the coherent processing interval, when observed by wideband radar with high range resolution. Two CFAR detectors are proposed assuming different correlation properties of clutter over range. The detectors' performance is studied via numerical simulations and a significant improvement over existing techniques is demonstrated.**

I. Introduction

Modern wideband radars have enabled a sub-meter range resolution, thus providing additional possibilities for target detection and classification [1], [2]. However, the target detection in high resolution mode has a few differences w.r.t. the detection in low range resolution mode. Namely, clutter becomes non-Gaussian, targets become range extended and also, fast-moving targets appear to have a range-walk (also called range migration) during the coherent processing interval (CPI).

The modern trend is to model the non-Gaussian clutter as a compound-Gaussian (CG) process, which allows to separate slow-time correlation characteristics of clutter from its PDF [2], and provides a mathematically tractable tool to derive detectors. Radar detection of point and extended targets has been extensively studied during the last decades, resulting in a number of handful detectors for the aforementioned scenarios [2]. Algorithms for covariance matrix (CM) estimation from the reference CG data complement the aforementioned detectors and make them adaptive [2], [3]. On the other hand, the target range-walk is generally not considered for target detection. For fast moving targets, which are of interest for radar, ignoring the range-walk results in the smearing of the target response in range and velocity [4]. Consequently, signal to clutter ratio (SCR) degrades, as well as the detection performance.

The aim of this paper is to derive CFAR detector for a range migrating target in a CG clutter. To do this, we develop two detectors considering, firstly, an independent and, secondly, a dependent interference model of the CG clutter, defined according to [5].

This paper is organized as follows. In Section II, we revise the target model and provide the problem formulation. Next, in Section III we derive a detector for the independent interference model (IIM), and then, in Section IV we consider the case of dependent interference model (DIM). The performance of the proposed techniques is evaluated in Section V and conclusions are given in Section VI.

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II. Data model

A. Target model

Assume a wideband radar to coherently transmit M wideband pulses. The signature of a point target, observed by the radar in a block of K adjacent range cells, can be expressed by $K \times M$ matrix $\mathbf{A}$ [4]:

$$\mathbf{A}_{k,m} = e^{jf_D T_r m} \cdot u_p \left(k - \left(k_0 - \frac{v_0 T_r}{\delta_R} m \right) \right), \quad (1)$$

where $m = 0 \dots M-1$ is the pulse (slow-time) index, $k = 0 \dots K-1$ is the range cell (fast-time) index, k_0 stands for the initial range cell of the target, moving with the constant radial velocity v_0, $f_D = 4\pi v_0 f_c / c$ is the Doppler frequency of the target at the lower frequency of the band (transmitted signal occupies frequencies from f_c to $f_c + B$), T_r is the pulse repetition interval (PRI), $\delta_R = c/(2B)$ is the radar range resolution, B is the bandwidth of the transmitted signal and $u_p(x)$ denotes the pulse response of the transmitted waveform. Herein we assume a waveform with a flat spectrum over the band, so $u_p(x) = \operatorname{sinc}(\pi x)$.

Because of the migration effect, the target amplitude estimation and, therefore, the detection should be performed over the low range resolution segment (LRRS) containing K adjacent range cells, such that the condition on maximal target velocity (V_{max}) holds:

$$K \geq [v_{max} M T_r / \delta_R] + \Delta_E, \quad (2)$$

where $[\cdot]$ stands for the rounding towards integer operation and Δ_E defines the extent of the target in range cells. In this paper, the problem of extended target detection is not considered, thus $\Delta_E = 1$.

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B. Notations and definitions

In this paper we use lowercase boldface letters for vectors and boldface uppercase letters for matrices, the scalars are denoted by non-bold letters. Most vectors have the size of the vectorized LRRS, so $KM \times 1$. Thus, for example, vectorized received data in the LRRS are denoted by $\mathbf{y}$, which is given element-wise by $\mathbf{y} = [y_0, y_1 \dots y_{KM-1}]^T$. Hereinafter we also refer to the block of data, corresponding to the k-th range cell by the sub-vector of length M: $\mathbf{y_k} = [y_{kM}, \dots, y_{(k+1)M-1}]^T$, so $\mathbf{y} = [\mathbf{y_0}^T, \mathbf{y_1}^T, \dots, \mathbf{y_{K-1}}^T]^T$. Similar notation holds for other $KM \times 1$ vectors.

Some variables are briefly described here:

- $\mathbf{a}$ - vectorized known steering vector of the target in the LRRS: $\mathbf{a} = \text{vec}(\mathbf{A}^T)$;
- $\mathbf{c}$ - vectorized response of CG clutter in the LRRS;
- $\mathbf{g}$ - vectorized response of speckle component in the LRRS;
- σ_k^2 - clutter texture (local power) in the k-th range cell;
- α - constant amplitude of a target in the LRRS under hypothesis of its presence (H_1);
- $\mathbf{M}$ - $KM \times KM$ CM of CG clutter in the LRRS.

C. Problem formulation

The detection problem can be formulated as:

$$\mathbf{y_k} = \begin{cases} H_0: & \mathbf{c_k} \\ H_1: & \alpha\mathbf{a_k} + \mathbf{c_k} \end{cases} \qquad k = 0 \dots K-1. \quad (3)$$

The clutter in each range cell is modeled as a CG random vector, i.e. a product of two independent random variables [2]: $\mathbf{c_k} = \sigma_k \mathbf{g_k}$. A priori knowledge about the distribution of texture σ_k^2 has been shown to provide a detection improvement for small M, but results in equivalent performance for $M > 16$ [6]. Moreover, the target range-walk can be observed only for large M, therefore, we consider σ_k^2 to be an unknown constant. The texture σ_k^2 is considered to be constant along slow-time, but different from one range cell to another. The speckle component $\mathbf{g}$ is modeled by $KM \times 1$ zero mean complex Gaussian vector.

In the following two section, we develop two detectors by considering the IIM and DIM of CG clutter.

III. Migrating target detection in CG clutter - independent interference model

A. Clutter model

According to the IIM, the clutter is considered to be uncorrelated over range. The speckle component in each range cell k is modeled as an independent M-dimensional complex Gaussian vector with zero mean and known CM: $\mathbf{g_k} \sim CN(0, \mathbf{M_v})$, so $E\{\mathbf{g_k}\mathbf{g_i}^H\}|_{k \neq i} = \mathbf{0}_M$ and $E\{\mathbf{c_k}\mathbf{c_i}^H\}|_{k \neq i} = \mathbf{0}_M$. The clutter CM in every range cells is then given by $E\{\mathbf{c_k}\mathbf{c_k}^H\} = \sigma_k^2 \mathbf{M_v}$; and the CM of clutter in a LRRS has block-diagonal structure:

$$\mathbf{M} = \begin{bmatrix} \sigma_0^2\mathbf{M_v} & \mathbf{0}_M & \cdots & \mathbf{0}_M \\ \mathbf{0}_M & \sigma_1^2\mathbf{M_v} & \cdots & \mathbf{0}_M \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_M & \mathbf{0}_M & \cdots & \sigma_{K-1}^2\mathbf{M_v} \end{bmatrix}. \quad (4)$$

B. Generalized likelihood ratio test (GLRT)

In order to derive the detector we perform the GLRT. Under both hypotheses, the clutter local powers $\sigma_{\mathcal{K}}^2$, where $\mathcal{K}: k = 0 \dots K-1$, are unknown; under H_1, α is also unknown. The likelihood function of the LRRS under H_1 has a form:

$$f_1(\mathbf{y}; \alpha, \sigma_{\mathcal{K}}^2) = \frac{\exp\left(-\sum_{k=0}^{K-1} \sigma_k^{-2} \left(\mathbf{y_k} - \alpha\mathbf{a_k}\right)^H \mathbf{M_v^{-1}} \left(\mathbf{y_k} - \alpha\mathbf{a_k}\right)\right)}{\pi^{KM} \left|\mathbf{M_v}\right|^K \prod_{k=0}^{K-1} \sigma_k^{2M}}, \quad (5)$$

and its counterpart under H_0 can be obtained from $f_0(\mathbf{y}; \sigma_{\mathcal{K}}^2) = f_1(\mathbf{y}; \alpha, \sigma_{\mathcal{K}}^2)|_{\alpha=0}$. Constructing GLRT:

$$\Lambda(\mathbf{y}) = \frac{f_1(\mathbf{y}; \alpha, \sigma_{\mathcal{K}}^2)}{f_0(\mathbf{y}; \sigma_{\mathcal{K}}^2)} \quad (6)$$

and maximizing it over all the unknown parameters we can find the estimation of clutter powers under H_0:

$$\left(\hat{\sigma}_k^{(0)}\right)^2 = \frac{\mathbf{y_k}^H \mathbf{M_v^{-1}} \mathbf{y_k}}{M}, \ \forall k \in \mathcal{K} \quad (7)$$

and under H_1:

$$\begin{cases} \hat{\alpha} = \frac{\sum_{k=0}^{K-1} \left(\hat{\sigma}_k^{(1)}\right)^{-2} \mathbf{a_k}^H \mathbf{M_v^{-1}} \mathbf{y_k}}{\sum_{k=0}^{K-1} \left(\hat{\sigma}_k^{(1)}\right)^{-2} \mathbf{a_k}^H \mathbf{M_v^{-1}} \mathbf{a_k}}, \\ \left(\hat{\sigma}_k^{(1)}\right)^2 = \frac{(\mathbf{y_k} - \hat{\alpha}\mathbf{a_k})^H \mathbf{M_v^{-1}} (\mathbf{y_k} - \hat{\alpha}\mathbf{a_k})}{M}, \ \forall k. \end{cases} \quad (8)$$

The solution under H_1 has to be found iteratively by the fixed point iteration for α or $\sigma_{\mathcal{K}}^2$. The resulting detector has a form:

$$\Lambda(\mathbf{y}) = \left(\prod_{k=0}^{K-1} \frac{\left(\hat{\sigma}_k^{(0)}\right)^2}{\left(\hat{\sigma}_k^{(1)}\right)^2}\right)^M \underset{H_0}{\overset{H_1}{\gtrless}} P_{FA}^{-\frac{M}{M-1}}, \quad (9)$$

which insures CFAR property w.r.t. CM structure $\mathbf{M_v}$ and clutter powers $\sigma_{\mathcal{K}}^2$, given the iterative estimation (8) has converged. The detection threshold can be easily checked by considering the particular case for $v_0 = 0$, when the detector can be written explicitly.

IV. Migrating target detection in CG clutter - dependent interference model

A. Clutter model

In the case of DIM, the clutter is correlated along range, thus $E\{\mathbf{c_k}\mathbf{c_i}^H\}|_{k \neq i} \neq \mathbf{0}_M$. The CG model, being a product of two random variables, gives three ways to model such a behavior: considering either

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the speckle component or texture to be correlated over range, or both of them. Herein we assume the clutter speckle to be correlated over range, while the texture to be independent from one range cell to another. This modeling is different from the approach used in [7], [2]. The reason to follow this approach is the following: when considering Gaussian clutter as a particular case of the CG clutter, the adaptive CFAR detector of a range-migrating target requires the estimation of $\mathbf{Q} = E\{\mathbf{g}\mathbf{g}^H\}$ - the $KM \times KM$ CM of the speckle component of clutter in the LRRS [8] (in case of Gaussian clutter, speckle CM is equal to clutter CM). This $\mathbf{Q}$ cannot be obtained from the CM in one range cell only, i.e. $\mathbf{M_v}$. Ignoring the cross-correlation between the range cells (by using $\mathbf{M_v}$) leads to the non-CFAR behavior, if the diagonal blocks are substituted with their estimations [9].

Thus, we assume the clutter textures to be different unknowns (as realizations of random variables), but the speckle component to be correlated along range. As a result, covariance and cross-covariance matrices of clutter in the range cells of the LRRS can be expressed:

$$E\{\mathbf{c_i}\mathbf{c_j}^H\} = \sigma_i\sigma_j E\{\mathbf{g_i}\mathbf{g_j}^H\} = \sigma_i\sigma_j \mathbf{Q_{i,j}}, \qquad (10)$$

where $\mathbf{Q_{i,j}}$ denotes $M \times M$ block of the speckle CM $\mathbf{Q}$, such that $\mathbf{Q_{i,j}} = \mathbf{Q}_{iM\ldots(i+1)M-1, jM\ldots(j+1)M-1}$. Every $M \times M$ block $\mathbf{Q_{i,j}}$ describes the correlation of the speckle component between the range cells i and j. According to these assumptions, the clutter CM in the LRRS has the following structure:

$$\mathbf{M} = \begin{bmatrix} \sigma_0^2\mathbf{Q_{0,0}} & \cdots & \sigma_0\sigma_{K-1}\mathbf{Q_{0,K-1}} \\ \vdots & \ddots & \vdots \\ \sigma_{K-1}\sigma_0\mathbf{Q_{K-1,0}} & \cdots & \sigma_{K-1}^2\mathbf{Q_{K-1,K-1}} \end{bmatrix}. \qquad (11)$$

Herein we assume $\mathbf{Q}$ to be a known Hermitian positive definite matrix and we derive a detector in terms of the GLRT. To simplify the further derivation, we introduce:

$$\mathbf{W} = \begin{bmatrix} \sigma_0\mathbf{I}_M & \mathbf{0}_M & \cdots & \mathbf{0}_M \\ \mathbf{0}_M & \sigma_1\mathbf{I}_M & \cdots & \mathbf{0}_M \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_M & \mathbf{0}_M & \cdots & \sigma_{K-1}\mathbf{I}_M \end{bmatrix}. \qquad (12)$$

Then, according to (11) we can write: $\mathbf{M} = \mathbf{WQW}$. Moreover, $\mathbf{M^{-1}} = \mathbf{W^{-1}Q^{-1}W^{-1}}$, or the same can be written block-wise, similar to (11) with i^{th}, j^{th} block of inverted CM being defined by $\mathbf{M_{i,j}^{-1}} = \sigma_i^{-1}\sigma_j^{-1}\mathbf{Q_{i,j}^{-1}}$ (Remark: notation $\mathbf{Q_{i,j}^{-1}}$ stands for the i^{th}, j^{th} block of $\mathbf{Q^{-1}}$). Similarly, the determinant of $\mathbf{M}$ can be given via the determinant of $\mathbf{Q}$ as: $|\mathbf{M}| = |\mathbf{W}|\,|\mathbf{Q}|\,|\mathbf{W}| = |\mathbf{Q}|\prod_{k=0}^{K-1}\sigma_k^{2M}$.

B. Generalized likelihood ratio test

The detection problem is the same as before, see (3), and we perform the GLRT in order to find a detector. The likelihood function of the LRRS under H_1 is:

$$f_1(\mathbf{y};\alpha,\sigma_\mathcal{K}) = \frac{\exp\left(-(\mathbf{y}-\alpha\mathbf{a})^H\mathbf{M^{-1}}(\mathbf{y}-\alpha\mathbf{a})\right)}{\pi^{KM}|\mathbf{Q}|\prod_{k=0}^{K-1}\sigma_k^{2M}} \qquad (13)$$

and similarly $f_0(\mathbf{y};\sigma_\mathcal{K}) = f_1(\mathbf{y};\alpha,\sigma_\mathcal{K})|_{\alpha=0}$. The logarithm of the likelihood function is:

$$\ln\left(f_1(\mathbf{y};\alpha,\sigma_\mathcal{K})\right) = -KM\ln\pi - \ln\left(|\mathbf{Q}|\prod_{k=0}^{K-1}\sigma_k^{2M}\right) - (\mathbf{y}-\alpha\mathbf{a})^H\mathbf{M^{-1}}(\mathbf{y}-\alpha\mathbf{a}), \qquad (14)$$

where the quadratic form in the last term depends on the unknown parameters.

Denote $\mu_{k,j} = (\mathbf{y_k}-\alpha\mathbf{a_k})^H\mathbf{M_{k,j}^{-1}}(\mathbf{y_j}-\alpha\mathbf{a_j})$, then

$$(\mathbf{y}-\alpha\mathbf{a})^H\mathbf{M^{-1}}(\mathbf{y}-\alpha\mathbf{a}) = \mu_{k,k} + 2\Re\left(\sum_{j=0,j\neq k}^{K-1}\mu_{k,j}\right) + \sum_{i=0,i\neq k}^{K-1}\sum_{j=0,j\neq k}^{K-1}\mu_{i,j}, \qquad (15)$$

where notation $\Re(\cdot)$ stands for the real part of a complex number. The same can be written in terms of the speckle CM $\mathbf{Q}$ using the notations $q_{k,j} = \sigma_k\sigma_j\mu_{k,j} = (\mathbf{y_k}-\alpha\mathbf{a_k})^H\mathbf{Q_{k,j}^{-1}}(\mathbf{y_j}-\alpha\mathbf{a_j})$:

$$(\mathbf{y}-\alpha\mathbf{a})^H\mathbf{M^{-1}}(\mathbf{y}-\alpha\mathbf{a}) = \frac{q_{k,k}}{\sigma_k^2} + 2\Re\left(\sum_{j=0,j\neq k}^{K-1}\frac{q_{k,j}}{\sigma_k\sigma_j}\right) + \sum_{i=0,i\neq k}^{K-1}\sum_{j=0,j\neq k}^{K-1}\frac{q_{i,j}}{\sigma_i\sigma_j}. \qquad (16)$$

Note that $q_{k,j}$ is independent of $\sigma_\mathcal{K}$; and that the last item in (16) represents terms independent of the data in the k-th range cell.

In order to find σ_k we take the derivative of (14) w.r.t. σ_k using (16) and set it to zero. The estimation of σ_k can be obtained by solving the quadratic equation:

$$\sigma_k^2 - \sigma_k\frac{\Re\left(\sum_{j=0,j\neq k}^{K-1}\sigma_j^{-1}q_{k,j}\right)}{M} - \frac{q_{k,k}}{M} = 0, \qquad (17)$$

which is dependent on $\sigma_{j\neq k}$ and it also depends on α under H_1. By denoting: $b = -\Re\left(\sum_{j=0,j\neq k}^{K-1}\sigma_j^{-1}q_{k,j}\right)/M$ and $c = -q_{k,k}/M$, we can see that each of K equations always has two real roots (under both hypotheses), as $b^2 - 4c > 0$. Moreover, from Vieta's formula for second order polynomial, it follows that the roots of (17) satisfies $\sigma_k^{[1]}\sigma_k^{[2]} = c < 0$, so only one root is positive, which is the one of interest. Then each σ_k has a unique solution, which can be obtained via the function of all the other local powers $\sigma_j|_{j=0\ldots K-1,j\neq k}$:

$$\hat{\sigma}_k^{(0)} = \frac{-b^{(0)} + \sqrt{(b^{(0)})^2 - 4c^{(0)}}}{2} = f\left(\sigma_{j=0\ldots K-1,j\neq k}^{(0)}\right). \qquad (18)$$

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Under H_0 we have K equations, which form a system with K unknowns, so they have a unique solution, which can be found iteratively by the fixed point iteration for system of equations.

Under H_1, we have K equations for σ_k:

$$\begin{aligned}\hat{\sigma}_k^{(1)} &= \frac{-b^{(1)} + \sqrt{(b^{(1)})^2 - 4c^{(1)}}}{2} \\ &= f\left(\alpha, \sigma_{j=0\ldots K-1, j\neq k}^{(1)}\right),\end{aligned} \tag{19}$$

which depend on $K+1$ unknowns: $\sigma_{\mathcal{K}}$ and α. In order to obtain a unique solution, we need to add the equation for α, which can be obtained from the GLRT:

$$\hat{\alpha} = \frac{\mathbf{a}^H \left(\hat{\mathbf{M}}^{(\mathbf{1})}\right)^{-\mathbf{1}} \mathbf{y}}{\mathbf{a}^H \left(\hat{\mathbf{M}}^{(\mathbf{1})}\right)^{-\mathbf{1}} \mathbf{a}}, \tag{20}$$

where $\hat{\mathbf{M}}^{(\mathbf{1})}$ is defined according to (11) with $\hat{\sigma}_k^{(1)}$ substituted for σ_k. The solution is thus calculated similarly to that under H_0.

In order to perform detection, the estimations $\hat{\sigma}_k^{(0)}, \hat{\sigma}_k^{(1)}$ and $\hat{\alpha}$ should be substituted into the GLRT (6). Some simplifications of the GLRT can be done. First, note that equation (17) can be rewritten in terms of $\mu_{k,j}$ as:

$$\sum_{j=0, j\neq k}^{K-1} \Re\left(\hat{\mu}_{kj}\right) + \hat{\mu}_{kk} = M. \tag{21}$$

Further, we write the quadratic form of (15) via the sums over rows as:

$$\begin{aligned}&(\mathbf{y} - \hat{\alpha}\mathbf{a})^H \left(\hat{\mathbf{M}}^{(\mathbf{1})}\right)^{-\mathbf{1}} (\mathbf{y} - \hat{\alpha}\mathbf{a}) \\ &= \sum_{k=0}^{K-1} \left(\hat{\mu}_{kk} + \sum_{j=0, j\neq k}^{K-1} \hat{\mu}_{kj}\right) = KM,\end{aligned} \tag{22}$$

where the second equality holds because of (21) and Hermitian structure of clutter CM. Similarly, under H_0: $\mathbf{y}^H \left(\hat{\mathbf{M}}^{(\mathbf{0})}\right)^{-\mathbf{1}} \mathbf{y} = KM$. Consequently, the exponential term of the likelihood functions (13) does not affect the detection. The GLRT has a form:

$$\Lambda = \prod_{k=0}^{K-1} \left(\frac{\hat{\sigma}_k^{(0)}}{\hat{\sigma}_k^{(1)}}\right)^{2M} \underset{H_0}{\overset{H_1}{\gtrless}} \lambda, \tag{23}$$

which is similar to the test in the case of IIM clutter (see (9)). However, the estimators involved in these detectors are generally different. If the clutter is uncorrelated over range, (9) and (23) are identical.

The advantage of the DIM detector (23) over the IIM algorithm (9) is that the former does not require the block-diagonal structure of the clutter CM. Therefore, an adaptive detector can be obtained from the DIM detector by substitution of the known speckle CM with its estimation. However, the statistical analysis of an adaptive detector, which exploits LRRS speckle CM estimated from the reference data, is out of the scope of this paper.

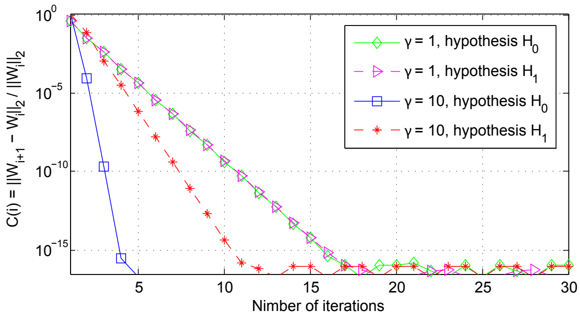

Figure 1. Convergence of iterative estimation in K-distributed clutter $\nu = 0.5$: $\gamma = 1$ corresponds to strongly correlated over range clutter; $\gamma = 10$ to clutter slightly correlated over range

V. Simulations

In this section the performance of the proposed algorithms is assessed by numerical simulations. The parameters of the radar are fixed to: $f_c = 10$ GHz, $B = 1$ GHz, $T_r = 1$ ms, $M = 32$; the maximum expected velocity of a target is: $|v_0| \leq v_a = c/(2f_cT_r)$, so we set $K = 5$ to satisfy (2). In all the simulations, the clutter follows K-distribution, a special case of CG, with shape parameter $\mu = 1$ and scale parameter $\nu = 0.5$.

A. Convergence analysis

We analyze the convergence by evaluating the widely used criterion

$$C(i) = \frac{||\hat{\mathbf{W}}_{i+1}^{(h)} - \hat{\mathbf{W}}_i^{(h)}||_2}{||\hat{\mathbf{W}}_i^{(h)}||_2} \tag{24}$$

by numerical simulations. Herein we denote by $\hat{\mathbf{W}}_i^{(h)}$ the estimation of the matrix $\mathbf{W}$ (12) at i-th iteration under hypothesis h. The known speckle CM has the structure $\mathbf{Q} = \mathbf{R} \otimes \mathbf{I}_M$ ($\otimes$ denotes Kronecker product), so the clutter is uncorrelated over slow time, but correlated over range. $\mathbf{R}$ is $K \times K$ symmetrical Toeplitz matrix defined by its first column $\mathbf{r}_k = \exp(-\gamma k)$ and describes the correlation of clutter speckle over range. Fig. 1 shows the convergence of the estimators (18), (19) for the case of range-correlated speckle: $\gamma = 1$; and almost uncorrelated over range speckle: $\gamma = 10$. Note that in both cases the convergence is linear and it is more rapid for weakly correlated clutter; in the limiting case ($\gamma \to +\infty$) the estimate under H_0 can be found explicitly (7).

B. False alarm regulation

Herein we check the CFAR properties of the proposed algorithms in a correlated CG clutter. We consider a scenario similar to the previous simulation with

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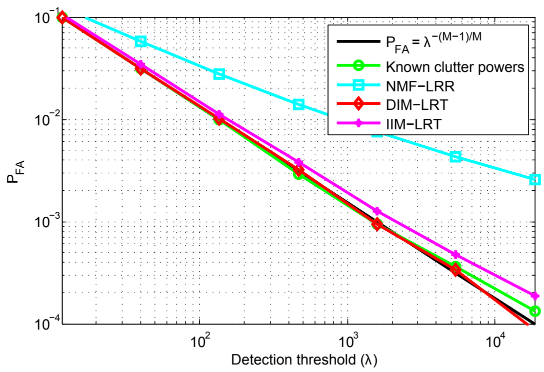

Figure 2. False alarm regulation in clutter strongly correlated over range $\gamma = 1$; K-distributed clutter $\nu = 0.5$

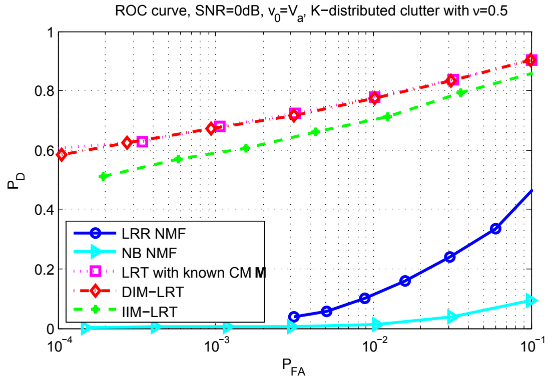

Figure 3. ROC curves for migrating target $v = v_a$, SCR=0 dB in K-distributed clutter $\nu = 0.5$, strongly correlated over range $\gamma = 1$

$\gamma = 1$ and we run 20 iterations of the estimators. We performed 10^3 of Monte-Carlo trials of $2KM$ different range-velocity cells. The P_{FA} regulation of four algorithms, namely IIM-LRT (9), DIM-LRT (23), NMF-LRT (normalized matched filter applied to the LLRS and using the speckle CM $\mathbf{Q}$) and the clairvoyant detector, assuming the known CM $\mathbf{M}$, are shown in Fig. 2. The line corresponding to

$$\lambda = P_{FA}^{-\frac{M}{M-1}}, \quad (25)$$

is also plotted. This line represents the threshold of IIM-LRT in IIM clutter (9). Fig. 2 shows that IIM-LRT and NMF-LRT are generally not CFAR in range correlated CG clutter, while DIM-LRT ensures CFAR property with the threshold defined by (25).

C. ROC curves

Similarly to a range-extended target detection in a CG clutter [2], the detection performance of range-migrating target will be dependent on the spread of the target response over range (hence for an extended target, non-coherent integration over range is performed, while for range migrating target, this integration is coherent). Thus, the performance of the proposed algorithms will be velocity-dependent. Due to the lack of space we omit this analysis here. However, in Fig. 3 we compare the performance of all the aforementioned detectors in terms of ROC curves for a target at velocity $v_0 = v_a$, SCR=0 dB after coherent integration and correlated clutter with $\gamma = 1$. A detector with the narrow-band target signature, ignoring migration term in (1) is also added for comparison (NB NMF). The results show that ignoring of target range-walk or clutter variation along range-walk results in severe degradation of the performance. The DIM detector achieves the performance of the detector with the clairvoyant CM, and the IIM detector have slightly worse performance than the DIM detector due to the ignorance of clutter range correlation.

VI. Conclusion

In this paper we have proposed two CFAR detectors of range-migrating target in a compound-Gaussian clutter. These algorithms involve iterative estimations of clutter local power, which have to be carried out numerically. The resulting detectors are functions of the received data and covariance matrix of the clutter speckle component only. The proposed detectors provide significant improvements over existing techniques in terms of ROC curves. Moreover, the proposed approach for dependent interference clutter model provides a way to develop an adaptive detector of range-migrating targets in a compound-Gaussian clutter, which is of practical interest.

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