GLRT DETECTION FOR RANGE AND DOPPLER DISTRIBUTED TARGETS IN NON-GAUSSIAN CLUTTER

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ABSTRACT

A Generalized likelihood ratio test (GLRT) is derived for adaptive detection of range and Doppler distributed targets. The clutter is modelled as a Spherically Invariant Random Process (SIRP) and its texture component is range dependent (heterogeneous clutter). We suppose here that the speckle component covariance matrix is known or estimated thanks to a secondary data set. Thus, unknown parameters to be estimated are local texture values, the complex amplitudes and frequencies of all scattering centers. The proposed detector assumes a priori *knowledge on the spatial distribution of the target and has the precious property of Constant False Alarm Rate (CFAR) with the assumption of a known speckle covariance matrix or by the use of frequency agility.*

1. INTRODUCTION

A High Range Resolution radar (HRR) can resolve a target into a number of scattering centers, depending on the range extent of the target and the range resolution of the radar. The range resolution is proportional to the inverse of the emitted bandwidth [1]. Different waveform can be used to achieve a high range resolution via pulse compression techniques. One may cite the chirp waveform which pulses are broadband thanks to a linear frequency-modulation, and the step frequency waveform that emits narrow band pulses centered on different frequencies to achieve a synthetic broad band.

In the last few years, many results have been obtained in radar detection with HRR. In particular, radar detection of distributed targets in white Gaussian noise [2], in Gaussian disturbance of unknown covariance matrix [3][4] and in non-Gaussian disturbance [5][6]. All these contributions show that a properly designed detector enables significant performances improvement which is based on several factors. Firstly, increasing the range resolution of the radar reduces the energy of the clutter in each range cell and secondly, resolved scatterers introduce less fluctuation than an unresolved point target.

However, in HRR mode, clutter statistics can't be modelled as Gaussian random process anymore due to the observation of spikes. The distribution is usually modelled as a compound Gaussian vector and more precisely, as a spherically invariant random vector (SIRV) [7]. The clutter vector is then the product of two components. A rapid fluctuation component so-called speckle which decorellation time is about 10ms and which can be decorrelated with the use of frequency agility. And a slow fluctuation component so-called texture that exhibits much longer decorrelation [8] time and which is not affected by frequency agility.

We propose here a detector which is designed for range and Doppler distributed targets in non-Gaussian clutter. Resolving the target on the Doppler axis enables to reduce the fluctuation of the scatterers with respect to a detector designed for range-only distributed targets. Moreover it enables to separate the target and clutter spectrum. This paper is organized as follows : in section 2, problem statement will be formulated and clutter and signal models will be described. The GLRT will be derived in section 3, CFAR property and false alarm probability will be discussed in section 4 and section 5 will be devoted to several results of the application of our detector on synthetic data.

2. PROBLEM STATEMENT AND SIGNAL MODEL

We assume that the target is spatially distributed over L range cells. The detection problem can thus be formulated as follows :

$$\begin{aligned} H_0 &: \quad \mathbf{z}_r = \mathbf{c}_r, \quad r = 1 \dots L \\ H_1 &: \quad \mathbf{z}_r = \mathbf{x}_r + \mathbf{c}_r, \quad r = 1 \dots L \end{aligned} \tag{1}$$

where $\mathbf{z}_r = (z_r(0), z_r(1), \dots, z_r(N-1))^t$. The observations are supposed to be independent between each range cell. The H_0 hypothesis corresponds to the only presence of clutter and the H_1 hypothesis to the presence of clutter and target.

2.1 Clutter subspace

The clutter $\mathbf{c}_r = \sqrt{\tau_r}\mathbf{s}_r$ is modelled as a Spherically Invariant Random Vector (SIRV) so that $\mathbf{s}_r = \mathscr{CN}(\mathbf{0}, \mathbf{M}), r = 1 \dots L$. $\mathbf{s}_r$ is commonly named *speckle* component, which covariance matrix $\mathbf{M}$ is here supposed to be known, estimated or identity with the use of frequency agility. τ_r, so-called *texture*, is a real positive random process. This representation is widely used to model the radar clutter [8][7][5][9]. The multivariate distribution of the clutter vector is given conditionally to the texture by :

$$p_{\mathbf{c}_r|\tau_r}(\mathbf{c}_r|\tau_r) = \frac{1}{(\pi\tau_r)^N \det \mathbf{M}} \exp\left(-\frac{\mathbf{c}_r^H \mathbf{M}^{-1} \mathbf{c}_r}{\tau_r}\right) \tag{2}$$

2.2 Signal subspace

The signal vector $\mathbf{x}_r = (x_r(0), x_r(1), \ldots, x_r(N-1))^t$ in each range cell, is the sum of the contribution of p_r scatterers so that :

$$x_r(n) = \sum_{k=1}^{p_r} a_{r,k} \exp\left(j\phi_{r,k}(n)\right), n = 0\ldots N-1 \quad (3)$$

Thus, the signal in each range cell can be expressed with matrix formulation as :

$$\mathbf{x}_r = \mathbf{E}_r \mathbf{a}_r \quad (4)$$

where $\mathbf{a}_r = (a_{r,1}, a_{r,2}, \ldots, a_{r,p_r})^t$ is the vector of complex amplitudes of the scatterers in the range cell. The signal vector $\mathbf{x}_r$ is equivalent to the so-called Gaussian linear model. This signal model has been often used in radar detection problem but also in array processing scenarios, see [9] for references. The steering matrix $\mathbf{E}_r$ is expressed as :

$$\mathbf{E}_r = \begin{pmatrix} 1 & 1 & \ldots & 1 \\ e^{j\phi_{r,1}(1)} & e^{j\phi_{r,2}(1)} & \ldots & e^{j\phi_{r,p_r}(1)} \\ \vdots & & & \vdots \\ e^{j\phi_{r,1}(N-1)} & e^{j\phi_{r,2}(N-1)} & \ldots & e^{j\phi_{r,p_r}(N-1)} \end{pmatrix} \quad (5)$$

It is assumed that the phase variation is linear so that :

$$\phi_{r,k}(n) = 2\pi f_{r,k} n, n = 0\ldots N-1 \quad (6)$$

With these definitions, and assuming $\mathbf{a}_r, r = 1, \ldots, L$ is deterministic, the observed signal distribution in each range cell is $\mathbf{z}_{r|\tau_r,H_1} \sim \mathscr{CN}(\mathbf{E}_r\mathbf{a}_r, \tau_r\mathbf{M})$. For the following developments, is is useful to consider the signal vector :

$$\mathbf{x}_r = \mathbf{U}_r \mathbf{b}_r, r = 1\ldots L \quad (7)$$

where, taking the singular value decomposition, $\mathbf{E}_r = \mathbf{U}_r\mathbf{S}_r\mathbf{V}_r^H, r = 1\ldots L$, $\mathbf{U}_r$ is the $N \times p_r$ unitary matrix of left singular vectors, $\mathbf{S}_r$ is the $p_r \times p_r$ diagonal matrix of non-zero singular values and $\mathbf{V}_r^H$ is the $p_r \times p_r$ diagonal unitary matrix of right singular vectors.

3. GLRT DERIVATION

3.1 Optimal detector and GLRT

Considering the independence hypothesis of the range cells, conditionally to the values of the texture component, the scatterers amplitudes and the steering matrix, the joint density under H_1 is :

$$p_{\mathbf{z}_{1:L}|\tau_{1:L},\mathbf{b}_{1:L},\mathbf{U}_{1:L},\mathbf{M},H_1}(\mathbf{z}_1, \ldots, \mathbf{z}_L | \tau_{1:L}, \mathbf{b}_{1:L}, \mathbf{U}_{1:L}, \mathbf{M}) = \prod_{r=1}^{L} \frac{\exp\left(-(\mathbf{z}_r - \mathbf{U}_r\mathbf{b}_r)^H \mathbf{M}^{-1}(\mathbf{z}_r - \mathbf{U}_r\mathbf{b}_r)/\tau_r\right)}{(\pi\tau_r)^N \det(\mathbf{M})} \quad (8)$$

and under H_0 :

$$p_{\mathbf{z}_{1:L}|\tau_{1:L},\mathbf{M},H_0}(\mathbf{z}_1, \ldots, \mathbf{z}_L | \tau_{1:L}, \mathbf{M}) = \prod_{r=1}^{L} \frac{1}{\tau_r^N \pi^N \det(\mathbf{M})} \exp\left(-\frac{\mathbf{z}_r^H \mathbf{M}^{-1}\mathbf{z}_r}{\tau_r}\right) \quad (9)$$

According to the Neyman-Pearson criterion, and assuming that the signal subspace $\mathbf{U}_r, r = 1\ldots L$ and clutter covariance matrix are known, the optimal detector is the likelihood ratio test which is obtained by integrating over all the values of the texture components :

$$\Lambda(\mathbf{z}_{1:L}) = \frac{E_{\tau_{1:L}}\{p_{\mathbf{z}_{1:L}|H_1}(\mathbf{z}_1, \ldots, \mathbf{z}_L | \tau_{1:L}, H_1)\}}{E_{\tau_{1:L}}\{p_{\mathbf{z}_{1:L}|H_0}(\mathbf{z}_1, \ldots, \mathbf{z}_L | \tau_{1:L})\}} \quad (10)$$
$$= \frac{\prod_{r=1}^{L} \int_0^\infty \frac{\exp\left(-(\mathbf{z}_r - \mathbf{U}_r\mathbf{b}_r)^H\mathbf{M}^{-1}(\mathbf{z}_r - \mathbf{U}_r\mathbf{b}_r)/\tau_r\right)}{\tau_r^N \det(\mathbf{M})} p_{\tau_r}(\tau_r) d\tau_r}{\prod_{r=1}^{L} \int_0^\infty \frac{1}{\tau_r^N \det(\mathbf{M})} \exp\left(-\frac{\mathbf{z}_r^H\mathbf{M}^{-1}\mathbf{z}_r}{\tau_r}\right) p_{\tau_r}(\tau_r) d\tau_r}$$

We do not know the multivariate distribution of the vectors $\mathbf{b}_r, r = 1\ldots L$, we have then modelled $\mathbf{b}_r, r = 1\ldots L$ as an unknown deterministic vector. In the same way, the texture component distribution can't be perfectly known or estimated and the presence of the integrals in the previous equation entails an heavy computational burden. We then propose to model it also as a deterministic vector and use a sub-optimum approach based on the generalized likelihood ratio test where the unknown parameters are replaced by their ML-estimates. We assume in this paper that the clutter covariance matrix is known (or estimated thanks to a secondary data set). The GLR is expressed as :

$$\Lambda_{GLRT}(\mathbf{z}_{1:L}) = \max_{\mathbf{U}_r, \mathbf{b}_r, \tau_r} \Lambda(\mathbf{z}_{1:L} | \mathbf{U}_r, \mathbf{b}_r, \tau_r) \quad (11)$$
$$= \Lambda(\mathbf{z}_{1:L} | \hat{\mathbf{U}}_r, \hat{\mathbf{b}}_r, \hat{\tau}_{r|H_1}, \hat{\tau}_{r|H_0})$$
$$= \frac{p_{\mathbf{z}_{1:L}|H_0}(\mathbf{z}_{1:L} - \hat{\mathbf{U}}_{1:L}\hat{\mathbf{b}}_{1:L} | \hat{\tau}_{1:L|H_1}, H_0)}{p_{\mathbf{z}_{1:L}|H_0}(\mathbf{z}_{1:L} | \hat{\tau}_{1:L|H_0}, H_0)}$$
$$= \frac{\prod_{r=1}^{L} \frac{1}{\hat{\tau}_{r|H_1}^N} \exp\left(-\frac{(\mathbf{z}_r - \hat{\mathbf{U}}_r\hat{\mathbf{b}}_r)^H\mathbf{M}^{-1}(\mathbf{z}_r - \hat{\mathbf{U}}_r\hat{\mathbf{b}}_r)}{\hat{\tau}_{r|H_1}}\right)}{\prod_{r=1}^{L} \frac{1}{\hat{\tau}_{r|H_0}^N} \exp\left(-\frac{\mathbf{z}_r^H\mathbf{M}^{-1}\mathbf{z}_r}{\hat{\tau}_{r|H_0}}\right)}$$

3.2 Parameter estimation

The ML estimation of $\mathbf{U}_r, r = 1\ldots L$ and consequently of the steering matrix $\mathbf{E}_r, r = 1\ldots L$ is not a straightforward problem. Indeed, no closed-form expression exists and numerical methods must be used. We have studied an EM-solution which enables to give an ML estimate but which computational complexity is prohibitive. That's the reason why we use spectral analysis methods such as the periodogram, AR models or high resolution spectral estimators which offers a good Doppler resolution. The estimation of Doppler frequencies is not discussed here but performances results of the detector with the use of superresolution spectral estimation methods are plotted in section 5.

After estimating the steering matrixes $\mathbf{E}_r, r = 1\ldots L$, we are able to give the ML-estimate of the scatterers complex amplitudes $\mathbf{b}_r, r = 1\ldots L$ and the texture component $\tau_r, r = 1\ldots L$. The ML-estimate of $\mathbf{b}_r, r = 1\ldots L$ under H_1 hypothesis is :

$$\hat{\mathbf{b}}_r = \arg\max_{\mathbf{b}_r} p_{\mathbf{z}_r - \mathbf{U}_r\mathbf{b}_r|\tau_r,H_0}(\mathbf{z}_r - \mathbf{U}_r\mathbf{b}_r | \tau_r, H_0)$$
$$= (\mathbf{U}_r^H\mathbf{M}^{-1}\mathbf{U}_r)^{-1}\mathbf{U}_r^H\mathbf{M}^{-1}\mathbf{z}_r, r = 1\ldots L \quad (12)$$

and the ML-estimate of the texture $\tau_{1\ldots L}$ under H_0 and H_1 are respectively :

$$\hat{\tau}_{r|H_0} = \arg\max_{\tau_r} p_{\mathbf{z}_r|\tau_r,H_0}(\mathbf{z}_r|\tau_r,H_0) = \frac{\mathbf{z}_r^H\mathbf{M}^{-1}\mathbf{z}_r}{N} \quad (13)$$

and, with (12) :

$$\hat{\tau}_{r|H_1} = \arg\max_{\tau_r} p_{\mathbf{z}_r|\tau_r,H_1}(\mathbf{z}_r|\tau_r,H_1) = \frac{\mathbf{z}_r^H(\mathbf{M}^{-1}-\mathbf{Q}_r)\mathbf{z}_r}{N} \quad (14)$$

where

$$\mathbf{Q}_r = \mathbf{M}^{-1}\mathbf{U}_r(\mathbf{U}_r^H\mathbf{M}^{-1}\mathbf{U}_r)^{-1}\mathbf{U}_r^H\mathbf{M}^{-1} \quad (15)$$

By injecting the ML-estimate of (12), (13) and (14) in (11), the generalized likelihood ratio test is reexpressed as :

$$\Lambda(\mathbf{Z}) = \frac{\prod_{r=1}^{L}(\mathbf{z}_r^H\mathbf{M}^{-1}\mathbf{z}_r)^N}{\prod_{r=1}^{L}(\mathbf{z}_r^H(\mathbf{M}^{-1}-\mathbf{Q}_r)\mathbf{z}_r)^N} \quad (16)$$

and, in an equivalent way, the generalized log-likelihood ratio is :

$$\ln\Lambda(\mathbf{Z}) = N\sum_{r=1}^{L}\ln\left(\frac{\mathbf{z}_r^H\mathbf{M}^{-1}\mathbf{z}_r}{\mathbf{z}_r^H(\mathbf{M}^{-1}-\mathbf{Q}_r)\mathbf{z}_r}\right) \quad (17)$$

It's interesting to note that the case $r=1$ and steering matrix reducing to a steering vector gives a GLRT expression identical to that given in [9] in the case of a point target in a compound Gaussian clutter. Moreover, considering a range-only distributed target, i.e. only with a steering vector per range cell, we find an equivalent expression to the one derived in [5].

4. FALSE ALARM PROBABILITY AND THRESHOLD ASSESSMENT

A detector owns the constant false alarm rate property (CFAR) when the detection threshold is independent of the clutter power. More generally, in the adaptive detection literature, the CFAR property refers to the clutter covariance matrix [10]. The derived detector is CFAR. Indeed, with the knowledge hypothesis of the covariance matrix $\mathbf{M}$ (estimated thanks to a secondary data set or being identity with an agile waveform), the GLRT is independent of the texture value. This is an important property which makes the detector adaptive. However, as we show in the following development, the detection threshold depends on the steering matrix and more precisely, of its rank i.e. the signal subspace dimension or the number of components.

We define the false alarm probability so that the log-likelihood ratio is higher than a threshold under H_0 :

$$P_{fa} = Pr\{\ln\Lambda(\mathbf{Z}|H_0)\rangle\,\eta\} \quad (18)$$

We then distinguish two cases :

– For $L=1$, we rewrite the log-likelihood ratio so that the numerator and denominator are independent :

$$\Gamma = \ln\Lambda(\mathbf{Z}|H_0,L=1) = N\ln\left(1+\frac{\mathbf{z}^H\mathbf{Q}\mathbf{z}}{\mathbf{z}^H(\mathbf{M}^{-1}-\mathbf{Q})\mathbf{z}}\right) \quad (19)$$

Under H_0, $\mathbf{z}=\mathbf{c}$. With the notation $\tilde{\mathbf{c}}$ the whitened clutter complex Gaussian vector, zero-mean and with identity covariance matrix, $\mathbf{z}=\sqrt{\tau}\mathbf{M}^{1/2}\tilde{\mathbf{c}}$. It's shown in [11] that the quadratic form $\tilde{\mathbf{c}}^H\mathbf{A}\tilde{\mathbf{c}}$ is chi-2 distributed with $2p$ degrees of freedom, p = rank of $\mathbf{A}$, if and only if $\mathbf{A}$ is idempotent, i.e. $\mathbf{A}^2=\mathbf{A}$. With this property, the numerator of the ratio into brackets in (19) is chi-2 distributed with $2p$ degrees of freedom. Indeed, $\mathbf{Q}$ is the orthogonal projector onto the signal subspace spanned by the columns of $\mathbf{U}$ of dimension p and is thus idempotent. In the same way, the denominator of the GRL is expressed by $\mathbf{z}^H(\mathbf{M}^{-1}-\mathbf{Q})\mathbf{z} = \tau\tilde{\mathbf{c}}^H(\mathbf{I}-\mathbf{Q}')\tilde{\mathbf{c}}$, where $\mathbf{Q}'$ is the orthogonal projector onto the subspace spanned by the columns of the whitened version of $\mathbf{U}$, i.e. $\mathbf{M}^{-1/2}\mathbf{U}$. $\mathbf{I}-\mathbf{Q}'$ is then the orthogonal projector onto the clutter subspace and its rank is $N-p$. Consequently the denominator of the ratio in (19) is chi-2 distributed with $2(N-p)$ degrees of freedom. Consequently :

$$\frac{\mathbf{z}^H\mathbf{Q}\mathbf{z}}{\mathbf{z}^H(\mathbf{M}^{-1}-\mathbf{Q})\mathbf{z}} \sim \frac{\chi^2(2p)}{\chi^2(2N-p)} \sim \frac{p}{N-p}F\left(2p,2(N-p)\right) \quad (20)$$

where $F(2p,2(N-p))$ is the well-known F-distribution. The probability density function of the log-likelihood ratio under H_0 is then, thanks to the jacobian transformation :

$$p_\Gamma(\Gamma) = f_1(\Gamma) = \frac{p}{N-p}e^{\Gamma}F_{2p,2(N-p)}\left(\frac{N-p}{p}(e^{\Gamma}-1)\right) \quad (21)$$

– For $L>1$, the log-likelihood ratio distribution is the convolution of previous distribution :

$$p\Gamma(\Gamma) = f_1(\Gamma) * f_2(\Gamma) * \ldots f_L(\Gamma) \quad (22)$$

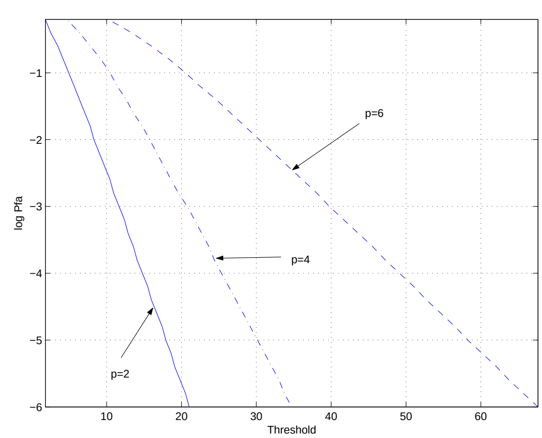

FIG. 1 – false alarm probability with respect to the detection threshold for L=1 and N=8.

The figure 1 represents the false alarm probability with respect to the threshold fixed for $N=8$, $L=1$ and different values of the signal subspace dimension p.

5. SIMULATION RESULTS

We present in this section the performances of our detector on synthetic signals in different scenarios. We compare it with the point target detector proposed in [9] and with the range-only distributed target detector of [5].

We consider a synthetic target which is distributed over $L = 4$ range cells and in each range cell, the scatterers are located at different normalized Doppler frequencies as represented in table 1. We fix unitary amplitudes for each scatterer.

TAB. 1 – Doppler frequencies of the scatterers.

cell #	1	2	3	4
frequencies	{0.1}	{0.1,0.2}	{0.1,0.2,0.3}	{0.1,0.2}

We resort to Monte-Carlo simulations to estimate the detection probability based on $100/P_d$ independent trials. The detection threshold is computed by inverting the distribution given in (22). The local value of the texture $\tau_r, r = 1 \ldots L$ is supposed to follow a gamma distribution :

$$p(\tau_r) = \frac{2b^\nu}{\Gamma(\nu)} \tau_r^{2\nu-1} \exp\left(-b^2\tau_r^2\right), r = 1 \ldots L \qquad (23)$$

where b controls the mean of the distribution and ν controls the deviation with respect to the Gaussian distribution. The higher ν is, the more Gaussian the distribution is. The clutter is then K-distributed. We fix in the following $\nu = 0.5$. The speckle covariance matrix corresponds to a Gaussian spectrum of 0.2 mean value and of 0.05 standard deviation. At last, we suppose that if the resolution is increased by L, then the clutter power in each range cell is divided by L with respect to a configuration where the target is fully contained in one range cell. The target total energy is $\mathscr{E} = \sum_{r=1}^{L} ||\mathbf{E}_r \mathbf{a}_r||^2$ and the signal to clutter ratio is :

$$SCR = \frac{\sum_{r=1}^{L} (\mathbf{E}_r \mathbf{a}_r)^H \mathbf{M}^{-1} (\mathbf{E}_r \mathbf{a}_r)}{N\sigma^2} \qquad (24)$$

where σ^2 is the clutter total energy.

The figure 2 presents the detection probability using the detector proposed, using the point target detector (considering that the radar resolution is decreased by a factor L) and using the range-only distributed target detector. The steering vectors of these last detectors are fixed on the normalized frequency 0.1, corresponding to the *base* of the target. The steering matrixes are known. We observe a performance gain of 12 dB with respect to the point target detector and approximatively 7 dB to the range-only distributed target detector (this gain is estimated at a detection probability of 0.5).

The figure 3 shows that the probability of detection increases with the parameter N, corresponding to the number of pulses integrated. The figure 4 plots the detection probability for different ν : $\nu = 1$, $\nu = 0.5$, $\nu = 0.3$ and $\nu = 0.2$. We can note that the detection probability increases when the clutter becomes more spiky, especially for low SCR. This result about the influence of ν is also observed in [5] and [6].

In previous simulations steering matrixes or steering vectors were assumed known. In a realistic scenario, this *a priori* knowledge is obviously not always straightforward and the

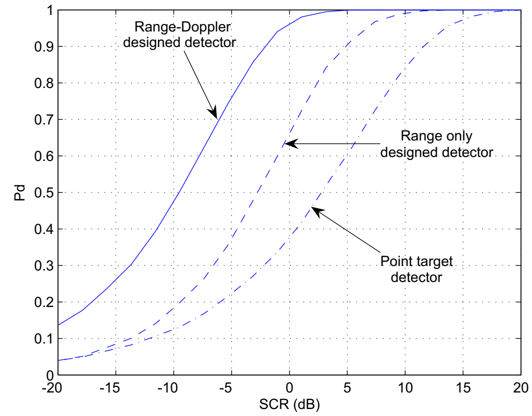

FIG. 2 – Comparison of the proposed detector designed for range and Doppler distributed target with respect to the point target detector and range-only distributed target detector for $N = 8$, $P_{fa} = 10^{-4}$.

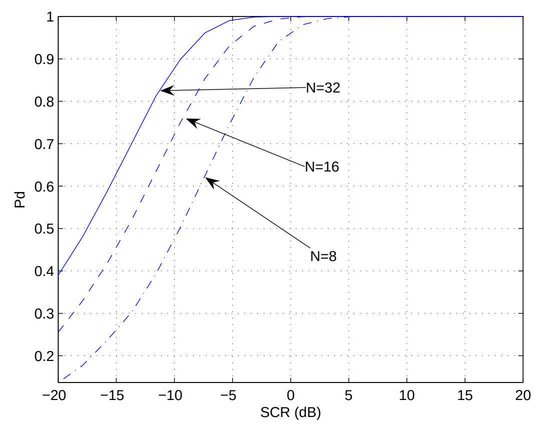

FIG. 3 – Influence of the number of integrated pulse N on the detection probability. $P_{fa} = 10^{-4}$.

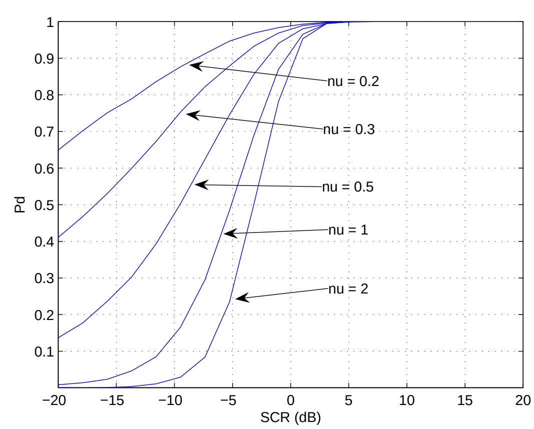

FIG. 4 – Influence of ν on the detection probability $P_{fa} = 10^{-4}$, $N = 8$.

signal subspace must be estimated. We have proposed in section 3.2 to use superresolution methods to estimate the Doppler frequencies of the signal components. These methods need the knowledge of the signal subspace dimension i.e. the number of signal components. To do so, we use Rissanen's MDL [13] criterion. We use LS-ESPRIT [12] that enables to give an estimate of the Doppler frequencies without having to search over the maxima of a function like MUSIC algorithm. In figure 5, the detection probability is plotted using ESPRIT algorithm for estimation. In order to save simulation time, the target considered is contained in one range cell and composed of three unitarian scattering points of respective normalized Doppler frequencies $\{0.1, 0.2, 0.3\}$. The threshold computed corresponds to a wanted $P_{fa} = 10^{-2}$. The data length is $N = 64$ samples in order to limit the error on frequency estimation. The correlation matrix is estimated thanks to forward-backward averaging or spatial smoothing technique. In order to take into account the frequency estimation error, we define the detection probability as the probability that the GLRT is higher than the threshold defined earlier and that the frequency estimation error is lower than the arbitrarily fixed value $1/N$, corresponding to the periodogram frequency resolution. Fig 5 shows that estimating the steering matrix yields a detection loss.

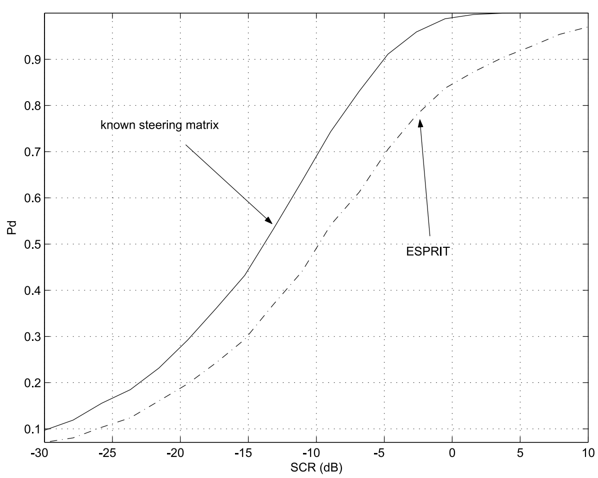

FIG. 5 – Comparison of the detector on target composed of 3 frequencies in one range cell in the case of known frequencies (solid curve) and ESPRIT estimated (dashdot curve). $P_{fa} = 10^{-2}$, $N = 64$, $\nu = 0.5$, $L = 1$.

6. CONCLUSION

We have proposed in this paper an adaptive detector for range and Doppler spread targets in non-Gaussian disturbance. The clutter is modelled as a spherically invariant random process (SIRP) with known or estimated speckle covariance matrix. The target steering matrix is also assumed to be known or estimated with spectral estimators such as ESPRIT. We consider that the local values of the texture component and the complex amplitudes of the targets are deterministic unknown parameters and are ML estimated so that the GLRT can be derived. We have shown that our detector, especially designed for range and Doppler distributed target enables performances enhancement with respect to low resolution detection or range-only target designed detectors.

Further research will be lead on evaluating the influence of clutter correlation and the influence of thermal noise added to the clutter. It would also be interesting to derive a detector without the range independency assumption of the different range cells.

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