

# Target Detection in Clutter Background: "Null" or "Whiten" the Clutter

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**Abstract**—In a clutter-dominant target detection problem, an adaptive detector prior to signal detection must either whiten or null the clutter. The former approach requires the estimates of covariance matrix of clutter while the latter only requires a proper set or estimate of the parameters of clutter subspace model. In this paper, we investigate the detection performance of a subspace-based detector and a sample covariance matrix(SCM)- based detector presented in [1] and [2], respectively, but for a mono-static radar system. Our simulation results show that the subspace-based detector not only can attain the predetermined false alarm probability (fully nulling clutter) but also offers better detection performance as compared with its counterpart. In this case, the SCM-based detector only offers better detection performance for detecting targets with Doppler frequency resided in clutter region as compared with that of subspace-based one.

**Index Terms**—Target detection, Clutter, False Alarm Regulation, GLRT.

## I. INTRODUCTION

There are two general target detection approaches in the presence of a clutter-dominant scenario. In the sample covariance matrix - based approach it is assumed that the clutter echo received in a range cell is the results of a large sum of contributions from different clutter scatterers, so it is asymptotically Gaussian with a specific structure of covariance matrix. In the second one, subspace-based approach, it is assumed received clutter echoes fallen within a specific subspace. Hence, the former approach requires the estimates of covariance matrix of clutter while the latter only requires a proper set the parameters of clutter subspace model. Generally speaking, it is preferable to null the clutter rather than whiten the clutter especially when (1) the dimensionality of the clutter subspace is small with respect to the number of pulses within a CPI(coherent processing interval), (2) the target signal to be detected is not substantially within the clutter subspace, and (3) in the nonhomogeneous clutter environment which invalidates the assumptions for estimating the clutter covariance matrix [1]- [6].

In distributed MIMO systems, we previously showed that geometry diversity of the distributed MIMO helps improve moving target detection since for a given target velocity, different transmit-receive pairs produce different Doppler frequencies that are less likely to be all small and reside in the clutter nulling region [1]. Based on this fact, we showed that the proposed subspace-based detector outperforms the one, which is based on a sample covariance matrix(SCM).

In this paper, we compare these two approaches when exploited for moving target detection in a monostatic radar system. To do this, we firstly compare the false alarm regulation of these approaches in the presence of a temporal clutter with power spectral density (PSD) of Gaussian to show the effectiveness of the subspace modeling to handel clutter. In other words, our simulation results show that subspace-based detector can attain the predetermined false alarm probability which means that subspace modeling of clutter can handel the clutter. In addition, in reality, it is probable to have range heterogeneity, which invalidates the assumption to estimate the clutter covariance matrix, so the degradation in detection performance of the SCM-based detector is expected, but the subspace based detector can not affected by this. All of these show the capability of the subspace-based detector to be exploited instead of the SCM-based detector in

practical situations.

The remainder of the paper is organized as follows. Section II is devoted to the detection problem statement. In Section III, we introduce two clutter models and then introduce two detectors working with these clutter models. In Section IV, we provide a comparison between two detectors we consider. Finally, conclusions are drawn in Section V.

*Notation* : Throughout the paper, scalars are denoted by non-boldface type, vectors by boldface lowercase letters, and matrices by boldface uppercase letters. Superscripts  $(\cdot)^T$ ,  $(\cdot)^*$  and  $(\cdot)^H$  denote transpose, complex conjugate and complex conjugate transpose, respectively. The the modulus of  $x$  is denoted by  $|x|$ .

## II. DETECTION PROBLEM STATEMENT

The problem of detecting a radar signal in the presence of receiver noise and clutter interference signals can be posed in terms of the following composite hypothesis testing problem

$$\begin{cases} \mathcal{H}_0 : \mathbf{r} = \mathbf{c} + \mathbf{w}, \\ \mathcal{H}_1 : \mathbf{r} = \alpha \mathbf{s}(f_d) + \mathbf{c} + \mathbf{w}, \end{cases} \quad (1)$$

where  $\mathbf{r}$  denote a  $K \times 1$  vector including the samples of the matched filter output within a CPI due to K transmitted pulses;  $\mathbf{c}$  denotes the clutter vector,  $\mathbf{w}$  denotes the noise vector distributed as  $\mathcal{CN}(\mathbf{0}, \sigma^2 \mathbf{I})$  with unknown variance  $\sigma^2$ ,  $\alpha$  is a complex unknown parameter accounting for both channel propagation effects and target backscattering, and  $\mathbf{s}(f_d)$  is the signal steering vector due to a Doppler frequency  $f_d$ , which is the Doppler shift due to the motion of target, given by

$$\mathbf{s}(f) = [1, e^{-j2\pi f_d T_{PRI}}, \dots, e^{-j2\pi(K-1)f_d T_{PRI}}]^T \quad (2)$$

where  $T_{PRI}$  is the time corresponding to the pulse repetition interval(PRI).

## III. CLUTTER MODEL

In this section, we introduce two clutter models. The first is to model clutter as a zero-mean complex Gaussian random process with specific temporal covariance matrix (general clutter model). The second is to model clutter with a known signature (clutter subspace model).

### A. General Clutter Model

Based on the fact that clutter echo received in a range cell is the results of a large sum of contributions from different clutter scatterers, it is asymptotically Gaussian. Such a model may apply to the returns from the forest, grassland, or other homogeneous surfaces. The clutter is also subject to internal motion such as wind. Thus, the received clutter echoes are complex Gaussian, and the temporal clutter fluctuations are slow compared with the observation interval of K pulses. Hence, in this general case, we assume the clutter to be zero-mean complex gaussian distributed with the following temporal correlation [2]

$$E\{\mathbf{c}\mathbf{c}^H\} = \mathbf{C}' \quad (3)$$

Then, the temporal correlation matrix of the received signal  $\mathbf{r}$  can be expressed as

$$\mathbf{C} = E\{\mathbf{r}\mathbf{r}^H\} = \mathbf{C}' + \sigma^2 \mathbf{I} \quad (4)$$

To proceed, it need to be described the choice of the clutter covariance matrix  $\mathbf{C}'$ . The temporal correlation of the clutter can be

characterized by its Doppler power spectral density (PSD) taking the form [7]

$$S(f) = p_c \left[ \frac{r}{r+1} \delta(f) + \frac{1}{r+1} \frac{\lambda}{2\sqrt{2\pi}\delta_v} \exp\left(-\frac{f^2\lambda^2}{8\delta_v^2}\right) \right] \quad (5)$$

where  $f$  is the Doppler frequency variable,  $\lambda$  the wavelength,  $r$  the ratio of dc power to ac power in the spectrum which depends on the radar frequency and wind speed,  $p_c$  the clutter power, and  $\delta_v$  the the root mean-square (RMS) of the clutter velocity. This relate to a continues autocorrelation function(ACF) as follows [2]

$$\phi(\tau) = p_c e^{-\pi^2 \tau^2 \left(\frac{8\delta_v^2}{\lambda^2}\right)} \quad (6)$$

The correlation coefficients related to the  $K$  consecutive sample is obtained by sampling the ACF at  $\tau = kT_{PRI}$  for  $k = 0, \dots, K-1$ , i.e.,  $\rho_c(k) = \phi(kT_{PRI})$ . Then clutter temporal correlation matrix is then given as

$$\mathbf{C}' = \begin{bmatrix} \rho_c(0) & \rho_c(1) & \cdots & \rho_c(K-1) \\ \rho(1) & \rho_c(0) & & \vdots \\ \vdots & & \ddots & \rho_c(1) \\ \rho_c(K-1) & \cdots & \rho_c(1) & \rho_c(0) \end{bmatrix}. \quad (7)$$

For the problem described above, the two-step generalized likelihood ratio test (GLRT) is to reject  $\mathcal{H}_0$  if [2]

$$L_{GLR}(\mathbf{r}) = \frac{|\mathbf{s}(f_d)^H \hat{\mathbf{C}}^{-1} \mathbf{r}|^2}{\mathbf{s}(f_d)^H \hat{\mathbf{C}}^{-1} \mathbf{s}(f_d)} > \eta_{SCM} \quad (8)$$

The threshold  $\eta_{SCM}$  is selected such that the desired  $P_{fa}$  requirement is satisfied. Here,  $\hat{\mathbf{C}}$  is known as sample covariance matrix (SCM) obtained as

$$\hat{\mathbf{C}} = \frac{1}{K_t} \sum_{k=1}^{K_t} \mathbf{r}_k \mathbf{r}_k^H \quad (9)$$

To estimate SCM, here, it is assumed that a secondary data set  $\{\mathbf{r}_k\}_{k=1}^{K_t}$  is available with the same covariance matrix as the vector  $\mathbf{r}$  and where such secondary data does not contain any useful signal.

### B. Clutter Subspace Model

In this case, the clutter are assumed to lie in the subspaces which is spanned by the columns of matrix  $\mathbf{H}$  with a dimension of  $K \times L$ , defined as [1], [4]

$$\mathbf{H} = [\mathbf{h}(f_1), \dots, \mathbf{h}(f_L)] \quad (10)$$

where  $\mathbf{h}(f_l) = [1, e^{-j2\pi f_l T_{PRI}}, \dots, e^{-j2\pi(K-1)f_l T_{PRI}}]^T$  and  $f_l$  are the Doppler frequencies in the low frequency region. Surface clutter usually has a small velocity spread due to the motion of the clutter scatterers, producing a small Doppler frequency spread for stationary radars. So, the clutter can be expressed as  $\mathbf{c} = \mathbf{H}\boldsymbol{\beta}$  where  $\boldsymbol{\beta}$  denotes the  $L \times 1$  complex and unknown coefficient vector associated with the clutter signature. Note that, the columns of the matrix  $\mathbf{H}$  must span the clutter subspace and the number of such vectors is determined by the Doppler spread of the clutter spectrum [1], [4], [5], [6]. Alternatively, given an upper bound on the bandwidth of the clutter spectrum, we can select  $f_l$  uniformly spread across the clutter bandwidth at frequencies of  $f_l = (l-1-Q)\Delta f_c$  with  $l = 1, \dots, Q$ , where  $Q$  and  $\Delta f_c$  are two parameters that should be selected properly in a practical situation to achieve a predetermined value for the false alarm probability [1], [5], [6].

In this case, the GLR test, which is also uniformly most powerful invariant (UMPI) test, can be expressed as [1]

$$L_{GLR_2}(\mathbf{r}) = \frac{|\mathbf{s}(f_d)^H \mathbf{\Pi}_{\mathbf{H}}^\perp \mathbf{r}|^2}{\left(\mathbf{s}(f_d)^H \mathbf{\Pi}_{\mathbf{H}}^\perp \mathbf{s}(f_d)\right) \left(\mathbf{r}^H \mathbf{\Pi}_{\mathbf{H}}^\perp \mathbf{r}\right)} > \eta_S \quad (11)$$

where  $\eta_S$  is a threshold determined according to a desired  $P_{fa}$  requirement.

## IV. PERFORMANCE RESULTS

In this section, several simulated scenarios are provided to verify the regulation of the false alarm rate and detection performance of the subspace GLR(S-GLR)detector and that of sample-covariance matrix GLR (SCM-GLR) one. In our simulation, the pulse repetition frequency is 500 Hz, the carrier frequency is 1 GHz and the number of pulses within a CPI is  $K = 12$ . For SCM-based GLR detector, we use  $K_t = 2K = 24$  range training data. The received input signal-to-noise ratio is also defined as

$$SNR_i = \frac{|\alpha|^2}{\sigma^2} \quad (12)$$

To show the effectiveness of the subspace-based detector in removing clutter, a simulation is arranged in which the received clutter over a CPI is modeled as (5) with parameters  $\delta_v = 1.5m/s$ ,  $r = 90$  and  $p_c = 40dB$ . In this case, the effect of selecting  $\Delta f_c$  and  $Q$  on the false alarm regulation of the proposed detector is analyzed in Fig. 1. This figure represents the  $P_{fa}$  versus frequency. The results show that in order to perfectly cancel clutter and to reach false alarm regulation, the Gaussian PSD of the simulated clutter should be modeled as a number of sinusoids at the Doppler frequency shifts of  $f_l = (l-1-Q)\Delta f_c$  Hz with  $\Delta f_c = 8Hz$ ,  $Q = 3$  where  $l = 1, \dots, Q$ . Also, the results with  $\Delta f_c = \frac{PRF}{K}$  with  $Q = 1$ , and  $\Delta f_c = 8Hz$  with  $Q = 2$  are all provided, which lead to  $P_{fa} > 10^{-3}$ . From the results presented in this section, we see the effectiveness of the subspace clutter model with proper selecting of the clutter region parameters, which able the subspace-based detector to achieve CFAR property without requiring any training data. In practical situations, it makes sense to consider a limited Doppler velocity extent(say clutter Doppler region) for receiving Doppler component of possible clutter echoes. Since the true Doppler component of the ground scatterers are unknown in practice and can take any values within that of the clutter Doppler region, it is logical to assume that we are faced with the worst case condition of receiving clutter echoes and, hence, consider all of the Doppler shifts of clutter Doppler region with selecting parameters  $\Delta f_c$  and  $Q$  properly. Like the selecting the order of MTI (Moving Target Indicator) filter, a radar designer can alter the parameters of the clutter region depending on the intended surveillance area.

In Fig. 2, we compare the detection performance of the S-GLR and the SCM-GLR detectors in terms of ROC curves for  $SNR_i = -3dB$  and  $2dB$ . It could be seen that the S-GLR detector provides better detection performance than that of the SCM-GLR detector even in homogenous situations. The results of Figs.1 and 2 demonstrate that the S-GLR detector not only provides the CFAR property but also outperforms the detection performance of the SCM-GLR detector. It is worth to note that the S-GLR detector does not need range training data.

To completeness, we compare the detection performance of the above detector as a function of Doppler frequency. The results are shown in Fig. 3 for  $P_{fa} = 10^{-3}$  and  $SNR_i = 2dB$ . It is seen that the SCM-GLR detector provides better target detection compared to the S-GLR detector only at the target Doppler frequencies resided in the clutter region.

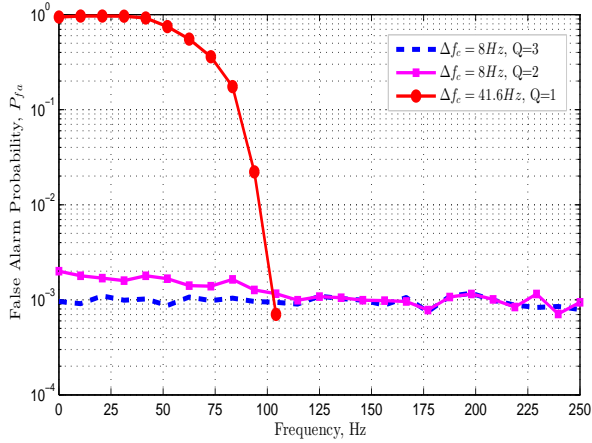


Fig. 1. False alarm regulation of the UMPI detector versus frequency, and  $Q$  and  $\Delta f_c$  as parameters.

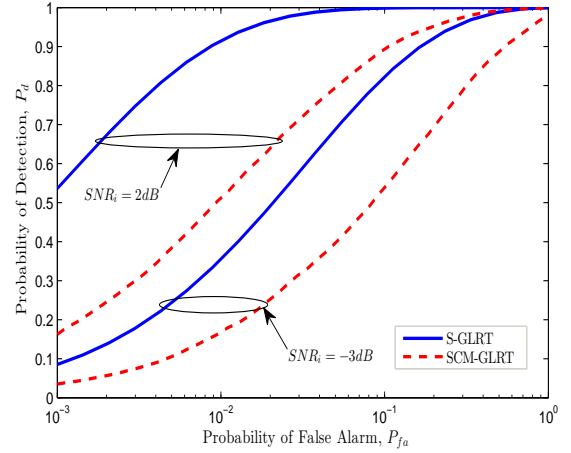


Fig. 4. Comparison of the S-GLR and the SCM-GLR detectors in terms of ROC curves for  $SNR_i = -3, 2dB$  in the presence of one interfering target in the training data with the same signal-to-noise ratio as that of desired target.

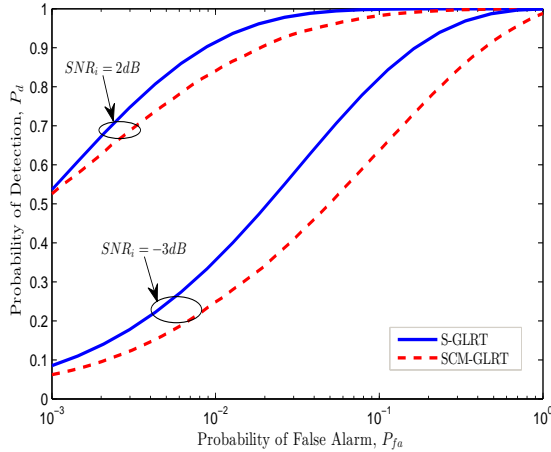


Fig. 2. Comparison of the S-GLR and the SCM-GLR detectors in terms of ROC curves for  $SNR_i = -3, 2dB$

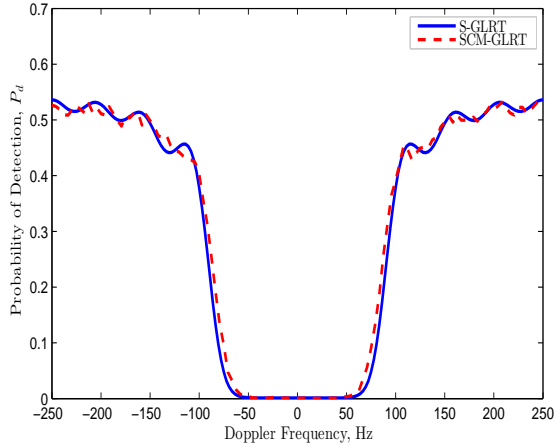


Fig. 3. Comparison of detection probability of the S-GLR and the SCM-GLR detectors as a function of Doppler frequency for  $SNR_i = 2dB$  and  $P_{fa} = 10^{-3}$ .

In the case of nonhomogeneous situations, it is expected that the

performance of the SCM-GLR detector degrades significantly since it invalidates the assumption of estimates of the covariance matrix. To show this, we consider a scenario in which one of the training range cells include an interfering target with the same signal-to-noise ratio as that of desired target. The results of this simulation is shown in Fig. 4. As expected, it is seen that the detection performance of the SCM-GLR detector degraded significantly especially when  $SNR_i = 2dB$ . In contrast, the S-GLR detector performs like what presented in Fig. 2, since S-GLRT has no need for training signals.

## V. CONCLUSIONS

In this paper, we investigated the capability of the subspace - based detector to be exploited in practical situations. To show this, we examine the subspace model of clutter, and show how to set parameters of this model to handel clutter. In this case, it is seen that the subspace detector not only well suited to handle clutter but also it has a superior performance as compared with the sample-covariance matrix(SCM)- based detector in nonhomogeneous situation. One advantage of the SCM-based detector over the subspace detector is it offers better detection performance for detecting targets with Doppler frequency resided in clutter region. This is done at the cost of more computational complexities since it requires to estimate and invert the sample covariance matrix, but the subspace detector needs to compute the projection matrix only once.

## REFERENCES

- [1] Zaimbashi, A., "Invariant Target Detection in Distributed MIMO Radar: Geometry Gain Helps Improving Moving Target Detection", *IET Radar, Sonar and Navigation*, (2015), 1-12.
- [2] He, Q., Lehmann, N. H., Blum, R. S., and Haimovich, A. M.: 'MIMO radar moving target detection in homogeneous clutter', *IEEE Trans. Aerosp. Electron. Syst.*, 2010, 46, (3), pp. 1290-1301
- [3] Raghavan, R.S.: 'Statistical interpretation of data adaptive clutter subspace estimation algorithm', *IEEE Trans. Aerosp. Electron. Syst.*, 2012, 48, (2), pp. 1370-1384
- [4] Wang, P., Li, H., and Himed, B.: 'Moving target detection using distributed MIMO radar in clutter with nonhomogeneous power', *IEEE Trans. Signal Process.*, 2011, 59, (10), pp. 4809-4820
- [5] Zaimbashi, A., Derakhtian, M., and Sheikhi, A.: 'GLRT-Based CFAR Detection in Passive Bistatic Radar', *IEEE Trans. Aerosp. Electron. Syst.*, 2013, 49, (1), pp. 134-159
- [6] Zaimbashi, A., Derakhtian, M., and Sheikhi, A.: 'Invariant Target Detection in Multiband FM-Based Passive Bistatic Radar', *IEEE Trans. Aerosp. Electron. Syst.*, 2014, 50, (1), pp. 720-736

- [7] Billingsley, J. B.: 'Low-Angle Land Clutter Measurements and Empirical Models', (IET, 2002)