Optimal Parameters and Performance Assessment for Detecting a Fluctuating Distributed-target

Tao Jian
Research Institute of Information Fusion, Naval Aeronautical and Astronautical University, Yantai 264001, China
Email: iamjiantao@yahoo.com.cn

Abstract—In high-resolution radar scenarios, the optimal detection of a fluctuating distributed-target is addressed, in a spherically invariant random vector clutter. The optimal binary integrator is derived from the generalized likelihood ratio test design procedure. The formula of the false alarm probability implies the constant false alarm rate property with respect to both the clutter power level and the covariance matrix. Moreover, the optimal detection parameter is also calculated. Finally, the detection performance is assessed by Monte Carlo simulation, which shows the effectiveness of the proposed detector. The experimental results also indicate that, as the number of sensors, the number of target equivalent scatterers or the clutter spikiness increases, the detection performance improves; while the detector performs robustly to different correlations of clutter.

Index Terms—target detection, performance assessment, fluctuating distributed-target, generalized likelihood ratio test, constant false alarm rate

I. INTRODUCTION

The low-resolution radar target echoes are confined to only one range resolution cell, which is modeled as a point-like target. The point-like target detection has been addressed partly in Gaussian background [1, 2, 3]. However, high-resolution radar can resolve a target into a number of scatterers by using pulse compression techniques, which is referred to as a distributed-target [4, 5, 6]. Increasing the radar range resolution can reduce the amount of energy per cell backscattered by distributed clutter and can enhance the radar detection performance largely by appropriate detection strategies [7, 8].

As the detection strategies of point-like targets may fail for distributed-targets, the distributed-target detection has gained more and more attention among the radar signal processing community. However, at a higher range resolution, the radar system receives non-Gaussian target-like spiky observations, which can be suitably modeled by a spherically invariant random vector (SIRV) [9, 10, 11, 12].

In this work, the optimal detection of a fluctuating distributed-target is addressed, based on the binary integrator (BI) and the generalized likelihood ratio test (GLRT) design procedure [13, 22, 23, 24]. In high-resolution radar scenarios, the optimal binary integrator is derived from the generalized likelihood ratio test design procedure. The formula of the false alarm probability implies the constant false alarm rate property with respect to both the clutter power level and the covariance matrix. Moreover, the optimal detection parameter is also calculated. Finally, the detection performance is assessed by Monte Carlo simulation, which shows the effectiveness of the proposed detector. The experimental results also indicate that, as the number of sensors, the number of target equivalent scatter or the clutter spikiness increases, the detection performance improves; while the detector performs robustly to different correlations of clutter.

This paper is organized as follows. In Section II, the target and clutter models are introduced, while the BI is derived in Section III. The performance assessment of the proposed detector is the object of Section IV, where the optimal threshold for BI is obtained and the performance is also given for different preferences. Finally, Section V contains some concluding remarks and hints for future work.

II. PROBLEM FORMULATION

It is assumed that data are collected from $N$ sensors and the problem of detecting the presence of a target across $K$ range cells $z$, $s$, $t = 1, \ldots, K$ is dealt with. It is supposed that the possible target is completely contained within those data [14]. Moreover, we mention that the resultant clutter residue power is significantly greater than the internal noise contribution. Herein, the clutter-dominant environment is considered, and the internal noise is ignored. Hence the detection problem to be solved can be formulated as the following binary hypotheses test

\[
\begin{align*}
H_0 & : z_t = c_t, \quad t = 1, \ldots, K \\
H_1 & : z_t = \alpha p + c_t, \quad t = 1, \ldots, K
\end{align*}
\]

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where $\mathbf{p}$ denotes the normalized steering vector, such that $\mathbf{p}^H \mathbf{p} = 1$ ($\cdot^H$ implies the conjugate transpose), and the $\alpha_i$, $s$, $t = 1, \ldots, K$ are unknown parameters accounting for both the target and the channel effects. Note that, for the uniform linear array [15],

$$
\mathbf{p} = \left(1, e^{j/\phi}, e^{j2\phi}, \ldots, e^{j(N-1)\phi}\right)^T \sqrt{N},
$$

where $\phi$ denotes a constant phase shifting and $\left(\cdot\right)^T$ represents transpose.

The clutter returns are modeled as a SIRV distribution for representing non-Gaussian clutter [9]. It is the product of a temporally and spatially “slowly varying” texture component, accounting for the reflectivity of the illuminated patches, times a “more rapidly” varying process due to the local validity of the central limit theorem [10–12]. Thus the $N$-dimension clutter vector $\mathbf{c}_t$ at range $t$ can be given by

$$
\mathbf{c}_t = \sqrt{r_t} \cdot \eta_t, \quad t = 1, \ldots, K + R
$$

where $\eta_t = (\eta_1(t), \eta_2(t), \ldots, \eta_N(t))^T$, $\eta_i(n)$ s, $n = 1, \ldots, N$ are zero-mean complex circular Gaussian random variables (RVs) with variance equal to one, and the texture component $r_t$ is a semipositive real RV with probability distribution $f_{r_t}$, which is called mixing distribution. The texture RV is used to model the large scatterers by BI, after single target scatterer detection in each range cell. Moreover, $\eta_t$ and $r_t$ are assumed to be independent from range cell to range cell. Here an $N \times N$ clutter covariance matrix structure $\mathbf{\Sigma}$ associated with $\eta_t$, $s$, $t = 1, \ldots, K + R$ is defined as

$$
\mathbf{\Sigma} = E \left\{ \eta_t \eta_t^H \right\}
$$

where $\mathbf{\Sigma}$ is the positive definite and Hermitian matrix, whose diagonal elements are equal to one.

It is assumed that the underlying mixing distribution $f_{r_t}$ is unknown. Thereby each component of clutter vector $\mathbf{c}_t$ is modeled as conditionally Gaussian with the unknown variance $\tau_t$. It is also assumed that $\alpha_i$ is unknown but $\mathbf{p}$ is known. According to the previous assumptions, the probability density function (PDF) of $\mathbf{z}_t$, $s$, $t = 1, \ldots, K$ under each hypothesis is given by [16]

$$
\begin{align*}
&f(z_t | \mathbf{\Sigma}, \tau_t, H_0) = \frac{1}{\pi^{n/2} \tau_t^n \det(\mathbf{\Sigma})} \\
&\quad \times \exp\left(-\frac{1}{\tau_t} \mathbf{z}_t^H \mathbf{\Sigma}^{-1} \mathbf{z}_t\right)
\end{align*}
$$

and

$$
\begin{align*}
&f(z_t | \mathbf{\Sigma}, \alpha_i, \tau_t, H_1) = \frac{1}{\pi^{n/2} \tau_t^n \det(\mathbf{\Sigma})} \\
&\quad \times \exp\left(-\frac{1}{\tau_t} (\mathbf{z}_t - \alpha_i \mathbf{p})^H \mathbf{\Sigma}^{-1} (\mathbf{z}_t - \alpha_i \mathbf{p})\right)
\end{align*}
$$

where $\det(\cdot)$ denotes the determinant.

According to the Neyman-Pearson criterion, the optimal solution to the hypotheses testing problem (1) is the likelihood ratio test, but for the case at hand, it cannot be implemented due to total ignorance of the parameters $\{\alpha_i \mid t = 1, \ldots, K\}$ and $\{\tau_t \mid t = 1, \ldots, K + R\}$. We can resort to the GLRT-based decision schemes [13]. Strictly speaking, the GLRT is tantamount to replace the unknown parameters with their maximum likelihood estimates under each hypothesis based on the entirety of data.

### III. Detector Design

In this section, under the assumption that the clutter covariance matrix structure $\mathbf{\Sigma}$ is known, the BI is derived.

To simplify the analysis, only one equivalent scatterer is supposed to occupy one resolution cell; in other words, the number of equivalent scatterers is equal to that of range cells occupied by target scatterers. In most cases of target scattering, the equivalent scatterers may occupy only a fraction of the $K$ range cells. Furthermore, the echo amplitudes of range cells occupied by target equivalent scatterers are significantly greater than that of range cells with clutter only.

The traditional detection strategies of a point-like target only utilize target energy in a single range cell, and may fail for distributed-targets. In order to make the best of target energy in all $K$ resolution cells of the range extent of target, we can accumulate target equivalent scatterers by BI, after single target scatterer detection in each range cell.

With known $\mathbf{\Sigma}$, the derivation of target scatterer detection in single range cell is begun by writing the GLRT as follows [13]

$$
\begin{align*}
&\max_{\alpha_i} \max_{\tau_t} \frac{f(z_t | \alpha_i, \tau_t, H_1)}{f(z_t | \tau_t, H_0)} \\
&= \max_{\tau_t} \max_{\alpha_i} \frac{1}{\tau_t} \exp\left[-\frac{1}{\tau_t} (\mathbf{z}_t - \alpha_i \mathbf{p})^H \mathbf{\Sigma}^{-1} (\mathbf{z}_t - \alpha_i \mathbf{p})\right] \\
&\quad \times \max_{\tau_t} \frac{1}{\tau_t} \exp\left[-\frac{1}{\tau_t} \mathbf{z}_t^H \mathbf{\Sigma}^{-1} \mathbf{z}_t\right]
\end{align*}
$$

By replacing the unknown parameters with their maximum likelihood estimates under each hypothesis [2, 17], the GLRT statistic for target scatterer detection in single range cell can be denoted as

$$
\lambda_i(z_t) = -N \ln \left[1 - \frac{\mathbf{p}^H \mathbf{\Sigma}^{-1} \mathbf{z}_t^2}{(\mathbf{z}_t^H \mathbf{\Sigma}^{-1} \mathbf{z}_t)(\mathbf{p}^H \mathbf{\Sigma}^{-1} \mathbf{p})}\right]
$$

Therefore, the first detection threshold $T_i$ of BI for the given first false alarm probability $P_{fa}$ can be given by [8, 17]

$$
P_{fa} = \exp\left[-\frac{(N-1)T_i}{N}\right]
$$

Set
\[ d_t = \begin{cases} 1, & \text{if } \lambda_t(z_t) > T_t \\ 0, & \text{otherwise} \end{cases}, \quad t = 1, \ldots, K \tag{9} \]

Herein, the BI (or M/K detector) is designed to detect all equivalent scatterers for distributed-target. The detection decision is based on at least M threshold crossings, out of K observations [18], where K is the integrated cell number and M (1 ≤ M ≤ K) is the threshold of BI. The first threshold level of a single range cell must be determined, for the given M and K, to produce the desired integrated false alarm probability \( P_{\text{fa}} \).

Since the choice of M affects this result, each M requires a different first threshold. It is necessary to determine an optimal or nearly optimal value for the parameter M.

The \( d_k \), \( s \), \( t = 1, \ldots, K \) are inputted into the M/K detector. Moreover, the hypothesis that a distributed-target is present is tested as follows

\[ \lambda_2 = \sum_{k=1}^{K} \frac{h_k}{T_2} d_k, \quad T_2 = M, \quad 1 \leq M \leq K \tag{10} \]

where the second detection threshold of BI is given by

To simplify the writing, the cumulative binomial probability distribution function, is denoted as

\[ E(K, M, p) = \sum_{k=0}^{M} (1-p)^{K-k}, \quad 1 \leq M \leq K, \quad 0 \leq p \leq 1 \tag{12} \]

where \( C_{k,K} \) is the binomial coefficient, which can be given by

\[ C_{k,K} = \frac{K!}{k!(K-k)!} \tag{13} \]

According to (12), the second false alarm probability \( P_{\text{fa}2} \) is simply expressed as

\[ P_{\text{fa}2} = E(K, M, P_{\text{fa}1}) \tag{14} \]

where \( P_{\text{fa}1} \) is the first false alarm probability in (8). For the given overall false alarm probability \( P_{\text{fa}} = P_{\text{fa}2} \), and \( K \), the first false alarm probability \( P_{\text{fa}1} \) can be determined from (14) either iteratively or approximately [18]. Finally, the first threshold \( T_1 \) can be computed from (8) for the given \( P_{\text{fa}} \). It is shown that both of two detection thresholds \( T_1 \) and \( T_2 \) are independent of \( \Sigma \) and \( r, s \), \( t = 1, \ldots, K \). It implies that, with the known \( \Sigma \), the BI is constant false alarm rate (CFAR) with respect to both the clutter covariance matrix structure and the clutter power level.

IV. PERFORMANCE ASSESSMENT

In this section, the optimal threshold of BI is calculated for detecting distributed-target with fluctuating scatterers. Furthermore, the detection performance of optimal BI is assessed in terms of different preferences.

The positive definite and Hermitian matrix \( \Sigma \) is assumed to be Toeplitz. The clutter samples were generated assuming an exponential correlation structure, i.e., Lorentzian spectrum, so that the matrix \( \Sigma \) has elements [12]

\[ \Sigma_{i,j} = \gamma^{i-j}, \quad 1 \leq i, j \leq N \tag{15} \]

where \( \gamma \) is the one-lag correlation coefficient.

For the underlying mixing distribution \( f_c \), the Gamma distribution is adopted with the following PDF

\[ f_c(x) = \frac{(L/b)^L}{\Gamma(L)} x^{L-1} e^{-((L/b)x)}, \quad x \geq 0 \tag{16} \]

where \( \Gamma(\cdot) \) is the Gamma function; \( b \) indicates the mean of the distribution; and \( L \) controls the deviation from Gaussian statistics. The smaller \( L \) is, the larger the tails of the distribution \( f_c \) are and the more spikes will appear in clutter. Without loss of generality, \( b \) is set to one, which merely normalizes the elemental clutter power to a specific value. With this mixing distribution, the statistics of the univariate amplitude of a clutter cell are described by the \( K \) distribution [19, 20].

It is assumed that each of the \( K \) range cells has a clutter component and each of the \( h_0 \) target range cells has a signal component. The quantity \( \sigma_s^2 / \sigma_c^2 \) indicates the average signal-to-clutter ratio (SCR) per range cell takes over \( K \) range cells. \( \sigma_s^2 \) and \( \sigma_c^2 \) indicate the average signal and clutter power per range cell respectively. The returns from target scatterers are modeled as independent and identically distributed (IID) zero-mean complex circular Gaussian RVs with the variance \( \sigma_s^2 \). In other words, it means that the target amplitude fluctuates with Rayleigh law over range cells. Because the target scatterers are modeled as IID RVs, the scatterer location distribution has no influence on the detection performance.

Moreover, the input SCR of distributed-target detectors is defined as [14]

\[ \text{SCR} = \frac{\sigma_s^2}{\sigma_c^2} p^H \Sigma^{-1} p \tag{17} \]

For the given \( P_{\text{fa}} \), \( M \) and \( K \), the first detection threshold of BI can be computed from (8). Moreover, the probability of detection \( P_d \) for the detector is estimated based on Monte Carlo simulation. For all results, numbers of Monte Carlos used to estimate each \( P_{\text{fa}} \) and \( P_d \) include 5000 and 100/\( P_{\text{fa}} \) (respectively) [21]. In order to limit the computational burden, it is assumed
that $P_{fa} = 10^{-4}$. For analytical convenience, $P_{fa}$ with different $M$ is given for $P_{fa} = 10^{-4}$ and $K = 15$ in Table I.

### TABLE I.

**VALUES OF $P_{fa}$ WITH DIFFERENT $M$ FOR $P_{fa}=10^{-4}$ AND $K=15$**

<table>
<thead>
<tr>
<th>$M$</th>
<th>$P_{fa}$ ($10^{-4}$)</th>
<th>$M$</th>
<th>$P_{fa}$ ($10^{-4}$)</th>
<th>$M$</th>
<th>$P_{fa}$ ($10^{-4}$)</th>
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<tr>
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<td>1.9723</td>
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<td>5.4117</td>
</tr>
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A. Optimal Detection Threshold

In this subsection, the optimal threshold $M$ ($M_{opt}$) of BI is calculated for distributed-target detection.

For only one equivalent scatterer is supposed to occupy one resolution cell, we just consider the values of $M$ for $M \leq h_0$. Herein, we present some representative $M_{opt}$ for $h_0 = 1, \ldots, 15$. In addition, $M_{opt}$ for other values of $h_0 \leq K$ has the similar rules and can be calculated from the resultant equation of $M_{opt}$ with respect to $h_0$.

In Fig.1, the plots of $P_d$ versus SCR of BI ($M = 1, 2, 3, 4, 5$) are given for $N = 2, L = 1, \gamma = 0, K = 15$ and $h_0 = 2$. It is observed that, the BI with $M = 2$ outperforms the BI with $M = 1$. We determine that $M_{opt} = 2$ for $h_0 = 2$.

Similarly, from Fig.2 to Fig.14, the detection performance of BI are given for $N = 2, L = 1, \gamma = 0, K = 15$ and $h_0 = 3, \ldots, 15$, respectively. For example, with the other preferences same as Fig.1, Fig.3 refers to the detection performance of BI ($M = 1, 2, 3, 4$) for $h_0 = 4$. It highlights that the BI with $M = 1$ performs worst, and the performance gets better as $M$ increases. Moreover, the BI with $M = 10$ performs best, but the performance gets worse as $M$ increases for $M \geq 3$. Hence, we determine that $M_{opt} = 3$ for $h_0 = 4$.

In particular, with the other preferences same as Fig.1, Fig.7 refers to the detection performance of BI ($M = 1, \ldots, 10$) for $h_0 = 10$. It is indicated that, the variational rules of detection performance of BI for $h_0 = 10$ are similar to those for $h_0 = 4$. For $M \leq 6$, the performance gets better as $M$ increases, however, for $M \geq 6$, the performance gets worse as $M$ increases. Thereby we determine that $M_{opt} = 6$ for $h_0 = 10$.

According to Fig.1–Fig.14, in like manner, we also calculate the optimal $M$ for other values of $h_0 \leq K$. As a result, the values of $M_{opt}$ with different $h_0$ are given for $K = 15$ in Table II. It is observed that $M_{opt}$ is a monotonically increasing function of $h_0$.

According to Table II, It is concluded that, for $1 < h_0 \leq K$, $M_{opt}$ satisfies the following equation

$$
M_{opt} = \text{round}\left(\frac{h_0}{2} + 1\right)
$$

where round(·) denotes rounding the parameter to the nearest integer.

### TABLE II.

**VALUES OF $M_{opt}$ WITH DIFFERENT $h_0$ FOR $K=15$**

<table>
<thead>
<tr>
<th>$h_0$</th>
<th>$M_{opt}$</th>
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<th>$M_{opt}$</th>
<th>$h_0$</th>
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<td>4</td>
<td>10</td>
<td>6</td>
<td>15</td>
<td>9</td>
</tr>
</tbody>
</table>

According to Table II, It is concluded that, for $1 < h_0 \leq K$, $M_{opt}$ satisfies the following equation

$$
M_{opt} = \text{round}\left(\frac{h_0}{2} + 1\right)
$$

where round(·) denotes rounding the parameter to the nearest integer.

Figure 1. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, h_0=2, P_{fa}=10^{-4}$.

Figure 2. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, h_0=3, P_{fa}=10^{-4}$. 

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Figure 3. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, h_0=4, P_{fa}=10^{-4}$

Figure 4. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, h_0=5, P_{fa}=10^{-4}$

Figure 5. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, 6, h_0=6, P_{fa}=10^{-4}$

Figure 6. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, 6, 7, h_0=7, P_{fa}=10^{-4}$

Figure 7. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, 6, 7, 8, h_0=8, P_{fa}=10^{-4}$

Figure 8. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, 6, 7, 8, 9, h_0=9, P_{fa}=10^{-4}$

Figure 9. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, 6, 7, 8, 9, 10, h_0=10, P_{fa}=10^{-4}$

Figure 10. $P_d$ versus SCR of BI for $N=2, L=1, \gamma=0, K=15, M=1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, h_0=11, P_{fa}=10^{-4}$
B. Influence of Different Preferences

In this subsection, the optimal BI with parameters in Table II is assessed in terms of different preferences.

First, in Fig.15, the detection performance of optimal BI are given for different numbers of target equivalent scatterers (h₀ = 2, 4, 6, 8, 10, 12, 15), with N = 2, L = 1, γ = 0 and K = 15. The figure shows that the detection performance is enhanced largely as the number of target scatterers h₀ increases, whereas the performance gain decreases as h₀ increases.

In particular, with other preferences same as Fig.15, Fig.16 refers to the detection performance of optimal BI with different numbers of sensors (N = 2, 4, 8, 16). The results indicate that the detection performance of optimal BI is improved as the number of sensors used N increases; while the performance gain decreases as N increases.

Remarkably, the performance curves with different one-lag correlation coefficients (γ = 0, 0.5, 0.9) nearly coincide in Fig.17. In other words, there is nearly the same detection performance with different clutter one-lag correlation coefficients, which shows the robustness of optimal BI to variation of the one-lag correlation coefficient.

Note that, the smaller L is, the larger the tails in the clutter distribution are. Finally, the effects of the clutter spikes are analyzed by varying L in Fig.18, where the curves of Pₐ versus SCR are given for L = 1, 2, 5. The figure highlights that the detection performance improves as L decreases. Herein we can give a heuristic interpretation. For a given Pᵣ, when L decreases, the clutter spikes increases and the energy that can be accumulated from the cells under test increases and the final Pₐ is improved. For a given level Pᵣ > 0.5, SCRᵣ required for L = 1 is 1–1.5dB less than that for L = 2, 5. However, it is also noted that, the mixing distribution fᵣ is nearly a Gaussian distribution for L ≥ 5, hence the detection performance for L ≥ 5 is expected to be almost the same.

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fluctuating scatterers is addressed, by exploiting the clutter spikiness increases, the detection performance improves; while the detector performs robustly to different correlations of clutter.

The capability of the proposed detectors in detecting slightly mismatched signal while rejecting unwanted signals [6] will be assessed in the future work.

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Tao Jian was born in Tianmen, Hubei Province, P.R. China. He received his B.S., M.S., and Ph.D. degrees in electronic engineering from Naval Aeronautical and Astronautical University at Yantai, China, in 2003, 2006, and 2011 respectively. Now he is a lecturer at Naval Aeronautical and Astronautical University at Yantai, China. His main research interests include radar signal detection and signal processing.