Optimizing distributed detection thresholds for multistatic radar systems

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ABSTRACT

In this paper, we propose an approach for optimizing distributed detection thresholds for multi-static radar systems. Under the Neyman-Pearson criterion, local detection thresholds are optimized using the Particle Swarm Optimization (PSO) algorithm. The local thresholds are optimized to maximize the overall detection probability under the constraint of a given overall false alarm probability. The advantages of PSO include its simplicity, few parameters, and efficient global search. Numerical simulation examples are provided for a radar system comprising two local stations for the distributed detection of targets in Gaussian clutter. The results indicate that the OR rule consistently serves as the optimal fusion rule, and thresholds are optimized flexibly to maintain the overall detection performance despite heterogeneous changes in the signal-to-clutter power ratio (SCR) at local stations. In some cases, local threshold optimization can be omitted without significant reduction in the overall system detection performance.

Keywords: Multistatic radar; Distributed Detection; Particle Swarm Optimization (PSO).

1. INTRODUCTION

Multistatic radar systems have many advantages, especially the ability to detect small targets, stealth, and combat high-tech electronic warfare [1]. Among the various system configurations, parallel configuration of distributed detection in multi-static radars has attracted much attention from researchers [2–4]. A distributed detection model has a number of advantages over a centralized detection model due to reduced bandwidth costs, high reliability, and a large coverage area; however, detection quality is still significantly improved [1]. In this study, we focus on a two-level parallel configuration consisting of local stations, and a fusion center (FC). Each local station makes a binary decision on target presence (in each spatial resolution cell) and transmits the decisions to the FC. In FC, the final target detection decision is made after fusion processing of local binary decisions.

The distributed detection problem has been widely studied in many studies on sensor networks. In [5], fusion rules at sensors were designed for the two-sensor distributed detection problem with conditionally independent observations. An optimal fusion rule for local detectors was proposed in [2]. In [7], distributed detection was also studied under the Neyman-Pearson criterion to design fusion rules and local detectors in FC. In [8], the design of local detectors and optimal fusion rules for distributed detection problems with binary decisions for parallel fusion systems were discussed in greater detail. Under the Bayesian and Neyman-Pearson criteria, [8] demonstrated that the optimal local decisions are binary quantizers based on likelihood ratios, and the optimal fusion is the weighted sum of the local decisions. In [9–11], model fusing distributed decisions was proposed for large sensor networks. Investigating correlation in local decisions, the examples in [12] demonstrated loss in target detection performance when the system was affected by correlated Gaussian and Laplace noise. Some studies [13-14] have attempted to synthesize optimal fusion rules under the influence of inherent correlation in local decisions. Recent works [15–18] have studied the problem of distributed detection when local decisions are statistically dependent. To simplify the problem, most of the aforementioned studies assumed homogeneity in local detection thresholds (of the binary quantizer or of the likelihood ratio). In reality, system and environmental parameters are not homogeneous between decentralized stations. Therefore, the assumption of uniformity in the local detection threshold is not reasonable; thus, the system incurs certain losses.

In this study, we attempted to optimize the local detection thresholds of multistatic radar systems in parallel configurations. The optimal thresholds are searched in the solution space using the swarm optimization algorithm to maximize the overall system performance under the Neyman-Pearson criterion. The remainder of this paper is organized as follows: Section 2 presents a formulation of the distributed detection problem and fusion rules in FC under the Neyman-Pearson criterion. Section 3 briefly introduces the standard PSO algorithm before proposing an algorithm to optimize local detection thresholds using PSO. In section 4, we investigate the effectiveness of the proposed algorithm using numerical examples. Finally, section 5 concludes the research problem and discusses future research directions.

2. PROBLEM

2.1. The distributed detection problem under the Neyman-Pearson criteria

Consider the target detection problem in a parallel configuration for distributed detection systems, as illustrated in figure 1. The received signals at each station, $r_i(t)$ $(i=1,2,...,n)$, go through the local processing steps. Then, local detectors make binary decisions $u_i(i=1,2,...,n)$ based on testing two statistical hypotheses H_j (j=0,1), and send the decisions to the FC. Finally, these decisions are fused together to provide a final decision u_0 regarding the presence (H_1) or absence (H_0) of a certain target (in each spartial-resolution cell).

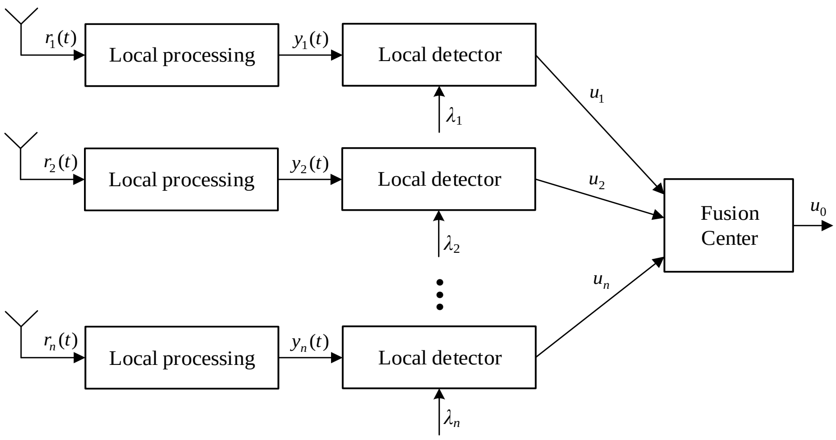

Figure 1. *Parallel configuration for distributed detection in multistatic radar systems.*

We consider a parametric detection problem where the probability density function of random variables y_i denoted by $f_i(y_i \mid H_{0,1})$ has completely known parameters. Accordingly, with the corresponding detection thresholds λ_i, local probabilities of false alarm P_{Fi} and detection P_{Di} are respectively given by:

$$P_{Fi} = P(u_i = 1 | H_0) = \int_{\lambda_i}^{+\infty} f_i(y_i | H_0) dy_i \tag{1}$$

$$P_{Di} = P(u_i = 1 | H_1) = \int_{\lambda_i}^{+\infty} f_i(y_i | H_1) dy_i \tag{2}$$

The local probabilities of missing a target are also given by:

$$P_{Mi} = 1 - P_{Di} \tag{3}$$

Let P_F and P_D be the respective overall probabilities of false alarm and detection, that is:

$$\begin{aligned} P_F &= P(u_0 = 1 | H_0) \\ P_D &= P(u_0 = 1 | H_1) \end{aligned} \tag{4}$$

Similarly, the overall probability of a miss is also given by:

$$P_M = 1 - P_D \tag{5}$$

To find the optimal fusion rule under the Neyman-Pearson criterion, the following constrained optimization problem must be solved:

$$\begin{aligned} &\min \quad P_M \\ &\text{s.t} \quad P_F = \alpha_0 \end{aligned} \tag{6}$$

where α_0 is a given overall probability of false alarm. The fusion rule and corresponding probabilities are derived as follows.

2.2. Fusion rules

This section derives expressions that determine the overall probabilities corresponding to each fusion rule for a distributed radar system with *n* stations under local thresholds. In general, the fusion rule is a logical function of *n* binary inputs with a single binary output. Thus, there are $L = 2^{2^n}$ rules when fusing *n* binary inputs at the center. For example, there are 16 fusion rules for combining two local decisions (as listed in table 1).

Table 1. *Fusion rules for the case of two local decisions.*

Inputs		Output u_0																Rules
u_1	u_2	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}	f
0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	d_3
0	1	0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1	d_2
1	0	0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1	d_1
1	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	d_0

As shown in table 1, the OR and AND rules are denoted by f_8 and f_2, respectively. If *f* is a certain fusion rule, meaning *f* is an integer, $0 \le f \le L-1$ and therefore can be represented in binary form of 2^n bits:

$$f = b' d_{2^n-1} ... d_1 d_0. \tag{7}$$

where b' is the symbol representing a binary number, and d_j denotes binary value of the *j-th* bit, with $j = 1, 2, ..., 2^n - 1$. A fusion rule at FC replaces the bits $\{d_0, d_1, ..., d_{2^n-1}\}$ with values of "0" or "1" at the corresponding position in *f*. Thus, fusion probabilities, P_F and P_M (and of course, P_D) are determined by:

$$P_F = \sum_{j=0}^{L-1} d_j \times P_e(u_1, u_2, ..., u_n \mid H_0) \tag{8}$$

$$P_M = \sum_{j=0}^{L-1} (1 - d_j) \times P_e(u_1, u_2, ..., u_n \mid H_1) \tag{9}$$

where $P_e(u_1, ..., u_n \mid H_{0,1})$ is the error probability caused by the decision vector $(u_1, ..., u_n)$ under hypotheses $H_{0,1}$, respectively. Assuming that local decisions are statistically independent, P_e is determined as follows:

$$P_e(u_1, ..., u_n \mid H_0) = \prod_{i=1}^{n} \left\{ P_{Fi}^{u_i} \times (1 - P_{Fi})^{1-u_i} \right\} \tag{10}$$

$$P_e(u_1, ..., u_n \mid H_1) = \prod_{i=1}^{n} \left\{ P_{Mi}^{1-u_i} \times (1 - P_{Mi})^{u_i} \right\} \tag{11}$$

Combining Eqs. (8) and (9) with (10) and (11), we obtain the final result that determines the overall probabilities of the system as follows:

$$P_F = \sum_{j=0}^{L-1} d_j \times \prod_{i=1}^{n} \left\{ P_{Fi}^{u_i} \times (1 - P_{Fi})^{1-u_i} \right\} \tag{12}$$

$$P_M = \sum_{j=0}^{L-1} (1 - d_j) \times \prod_{i=1}^{n} \left\{ P_{Mi}^{1-u_i} \times (1 - P_{Mi})^{u_i} \right\} \tag{13}$$

Because P_{Fi} and P_{Mi} $(i = 1, 2, ..., n)$ are functions that depend on thresholds λ_i, then P_F and P_M are multivariate functions that depend on both local thresholds and the fusion rule *f*. Then, optimization problem (6) can be rewritten as follows:

$$\begin{aligned} \min \quad & P_M = h(\lambda_1, \lambda_2, ..., \lambda_n, f) \\ \text{s.t} \quad & P_F = g(\lambda_1, \lambda_2, ..., \lambda_n, f) = \alpha_0 \\ & \lambda_i \in \mathbb{R}, i = \overline{1, n} \\ & f \in \mathbb{Z}, 0 \le f \le L \end{aligned} \tag{14}$$

3. PSO ALGORITHM OPTIMIZING DISTRIBUTED DETECTION THRESHOLDS

3.1. PSO algorithm

The PSO algorithm, introduced by Kennedy and Eberhart [19-20] in 1995, is inspired by the social and cognitive behavior of herds in biology. The power of this technique derives from the ability to simply calculate and share information between individuals in the same population, as well as global decisions of the population. The particles fly in a multi-dimensional search space, with each particle representing a possible solution to the multi-dimensional problem. The reasonableness of each solution is based on the multi-objective cost function related to the optimization problem that must be solved.

The movement of individuals is influenced by two factors that use information between iterations and between particles. Accordingly, each individual stores its own best solution, called *pbest*, and its current parameters are used to search the solution space. At the same time, the best solution for comparing particles is stored, called *gbest*, along with the current parameters of this solution. These two factors were considered the cognitive and social factors of the algorithm, respectively. After each iteration, *pbest* and *gbest* are updated for each particle if a better solution is found (more suitable according to the cost function). This procedure is repeated until the desired result converges or it can be determined that no other acceptable solution is found within the computational limits.

Several improved versions of the proposed PSO algorithm, aimed at increasing the convergence and accuracy of the algorithm, have been proposed [21–24]. However, this study does not attempt to improve the algorithm; instead, it employs the original PSO algorithm with small changes in inertia coefficients. With PSO, a group of particles flies in *d*-dimensional space to search for the optimal solution. Hence, the *k-th* particle has a current velocity vector denoted by $\mathbf{V}_k = [v_{k1}, v_{k2}, ..., v_{kd}]$ and a current position vector (solution) $\mathbf{X}_k = [x_{k1}, x_{k2}, ..., x_{kd}]$, where *d* is the dimension of the problem. PSO algorithms begin with random initialization of $\mathbf{V}_i$ and $\mathbf{X}_i$. In each iteration, the *k-th* particle optimal solution, $pbest_k = [p_{k1}, p_{k2}, ..., p_{kd}]$ and the population optimization solution, $gbest = [pg_1, pg_2, ..., pg_d]$ will lead the *k-th* particle according to (15) and (16) to update its velocity and position.

$$v_{ki}^{(t+1)} = \omega \times v_{ki}^{(t)} + U[0,1] \times w_1^{(t)} \times (p_{ki}^{(t)} - x_{ki}^{(t)}) + U[0,1] \times w_2^{(t)} \times (pg_i^{(t)} - x_{ki}^{(t)}) \quad (15)$$

$$x_{ki}^{(t+1)} = x_{ki}^{(t)} + v_{ki}^{(t+1)} \quad (16)$$

where ω is the inertia weight utilized to balance the local exploitation and global exploration, $U[0,1]$ is a uniformly distributed random number sample over [0,1], *t* denotes the index of iterations, w_1 and w_2 is the inertia coefficients that determine the influence of the best particle solution and the best population solution on the current velocity of each particle, respectively. More detailed analysis can be found in the literature [18–24].

3.2. Optimizing distributed detection thresholds using PSO

From the optimization problem analyzed in section 2, we can optimize local thresholds $(\lambda_1, \lambda_2, ..., \lambda_n)$ and fusion rule *f* simultaneously. However, the aim is to analyze fusion rules, local threshold vector is optimized for each possible fusion rule. Accordingly, for each rule *f*, particles have dimensions of *n*, where *n* is the number of local stations (the number of local detectors, respectively) in the multistatic radar system. Each dimension corresponds to a threshold λ_i, at which local detectors make decisions u_i $(i = 1, 2, ..., n)$. Therefore, each particle in the proposed PSO algorithm is denoted by $\mathbf{X}_k = [\lambda_1, \lambda_2, ..., \lambda_n]$. Threshold levels have continuous and finite values, depending on the statistical model of the amplitude of y_i. Note that the fusion rule f is an integer whose value satisfies $0 \le f \le L-1$. With each fusion rule *f*, the objective function of this problem is given by (13). Thus, we set up a constrained optimization problem with the goal of minimizing P_M with the condition $P_F = \alpha_0$. At each iteration, the particles' memory is updated if they find a solution that P_M is less than the previous value. The particles move in the solution space based on the expressions (15) and (16). These steps are repeated until convergence or the initial requirements are satisfied.

PSO algorithm to optimize distributed detection thresholds

Start PSO

1. Initialize the statistical model parameters of y_i, PSO parameters.
2. Initialize K particles randomly, where each particle represents a solution, $\mathbf{X}_k = [\lambda_1, \lambda_2, ..., \lambda_n]$. Initialize $pbest_k$ to be same.
3. The constraints are checked, and the objective function is calculated as follows:
   For each particle *k*:
   a. Calculate P_{Fi} for $i = 1, 2, ..., n-1$ using Eq. (1)
   b. Determine P_{Fn} from (12) and the constraints in Eq. (14)
   c. Obtain λ_n using Eq. (1)
   d. Obtain P_{Mi} for $i = 1, 2, ..., n$ using Eqs. (2) and (3)
   e. Determine P_M using Eq. (13)
4. The global solution is determined by the particle having the smallest P_M, *gpest*
5. Main loop:
   For $t = (1, 2, ..., T)$ (where *T* is the max. bound of the number on iterations)
      For $k = (1, 2, ..., K)$ (where *K* is the population size)
         For $i = (1, 2, ..., n)$ (where *n* is the problem dimensionality)
            Update the velocity using Eq. (15)
            The positions are updated using Eq. (16)
         End for *i*.
         The constraint is checked, and the cost function for each particle is calculated as in Step 3.
         Update $pbest_k$ if quality improves
      End for *k*.
      Update *gpest* if quality improves.
      Finish if *gpest* meets problem requirements.
   End for *t*.

End PSO.

In some specific cases, the initial limits of the solutions can be calculated in advance such that the loops do not fall into a suspended state, or it is difficult to find solutions that satisfy the constraints.

4. RESULTS AND DISCUSSION

4.1. Input data

We will consider the target detection problem in a Gaussian clutter environment using a multistatic radar configuration consisting of two distributed detection local stations, as shown in figure 1. Assuming local processing consists of only linear stages and an envelope detector, the input signal to local detectors, y_i (i=1,2) has a Rayleigh distribution. Assume these signals are statistically independent. The probability density functions of y_i under the two hypotheses $H_{0,1}$ are, respectively:

$$f_i(y_i \mid H_0) = \frac{y_i}{\sigma_i^2}\exp\left(-\frac{y_i^2}{2\sigma_i^2}\right) \tag{17}$$

$$f_i(y_i \mid H_1) = \frac{y_i}{\sigma_i^2(1+s_i)}\exp\left(-\frac{y_i^2}{2\sigma_i^2(1+s_i)}\right) \tag{18}$$

where σ_i^2 is the average power of the clutter and s_i is SCR. There is no loss of generality; Thus, we let $\bar{y}_i = y_i / \sigma_i$ be the signal normalized by the noise power at the input to the local detectors. Then, (17) and (18) are transformed into the following standardized form:

$$f_i(\bar{y}_i \mid H_0) = \bar{y}_i e\left(-\frac{\bar{y}_i^2}{2}\right) \tag{19}$$

$$f_i(\bar{y}_i \mid H_1) = \frac{\bar{y}_i}{(1+s_i)}\exp\left(-\frac{\bar{y}_i^2}{2(1+s_i)}\right) \tag{20}$$

From here, the expressions for determining the local probabilities (1), (2), (3) and the optimization problem are presented according to the standardized threshold levels, $\bar{\lambda}_i$.

Under the assumption of statistical independence between local decisions and the conditions $P_{Di} \gg P_{Fi}$ supported $\forall i = \overline{1,n}$, the optimal fusion rule is monotonic (details can be found in [1]). Therefore, only six of the 16 rules need to be considered, namely f_1, f_2, f_4, f_6, f_8 and f_{16}. However, it is easy to see that f_1 and f_{16} are not reasonable fusion rules under the Neyman-Pearson criterion. In addition, rules f_4 and f_6 involve only the decision of one of the two local stations and ignore the other stations. In this case, the optimization problem may reduce dimensionality, so we do not consider it here. Finally, there are only two rules, namely f_2 (AND) and f_8 (OR), that need to be further considered to determine the optimal fusion rule.

The error probabilities, P_F and P_M, are expanded from (12) and (13) as follows:

$$P_F = P_{F1} + P_{F2} - P_{F1}P_{F2} \quad \text{and} \quad P_M = P_{M1}P_{M2} \quad \text{(OR)} \tag{21}$$

$$P_F = P_{F1}P_{F2} \quad \text{and} \quad P_M = P_{M1} + P_{M2} - P_{M1}P_{M2} \quad \text{(AND)} \tag{22}$$

Next, the PSO algorithm (section 3.2) is employed to optimize the (normalized) detection thresholds for each fusion rule. Here, the PSO parameters used are: $\omega = 0.98$,

$T = 30$, $K = 30$ and $w_1 = w_2 = 2.0$ with a given false alarm probability, $\alpha_0 = 10^{-6}$.

4.2. Simulation results and comments

Table 2 presents the optimization results of the (normalized) local detection thresholds and the local false alarm probabilities for the OR rule at several SCR levels of s_1 and s_2. It can be observed that at fixed values of s_2, as s_1 increases, the threshold of detector 1 decreases, while that of detector 2 increases. Due to symmetry, the converse is also true, namely that at fixed values of s_1, if s_2 increases, the threshold of detector 2 decreases, while that of detector 1 increases. This is the result of optimizing the local false alarm probabilities to (21) satisfy the constraint $P_F = \alpha_0 = 10^{-6}$.

Table 2. *Optimized local thresholds and false alarm probabilities at several SCR values.*

s_2 (dB)	5			10			15		
s_1 (dB)	6	12	24	6	12	24	6	12	24
$\bar{\lambda}_1$ (dB)	5.3482	5.2764	5.2684	5.5406	5.3606	5.4725	5.6290	5.4119	5.3675
$\bar{\lambda}_2$ (dB)	5.4439	5.6788	5.7656	5.3025	5.4171	5.4725	5.2833	5.3649	5.4082
P_{F1}	6.3×10^{-7}	9.0×10^{-7}	9.4×10^{-7}	2.2×10^{-7}	5.8×10^{-7}	6.9×10^{-7}	1.3×10^{-7}	4.5×10^{-7}	5.6×10^{-7}
P_{F2}	3.7×10^{-7}	9.9×10^{-8}	6.0×10^{-8}	7.8×10^{-7}	5.8×10^{-7}	3.1×10^{-7}	8.7×10^{-7}	5.6×10^{-7}	4.5×10^{-7}

Figures 2 and 3 illustrate the relationships between the optimal local thresholds and false alarm probabilities versus SCRs. Figure 2 shows the local detection thresholds as a function of s_2 and parameter s_1. The local false alarm probabilities are also expressed as functions of s_2 with some given parameters of s_1. Based on these graphs, it is easy to see that when $s_1 = s_2$, the local false alarm probabilities and detection thresholds tend to approach each other. At this point, the problem returns to the case of homogeneous thresholds, which have been studied in previous studies.

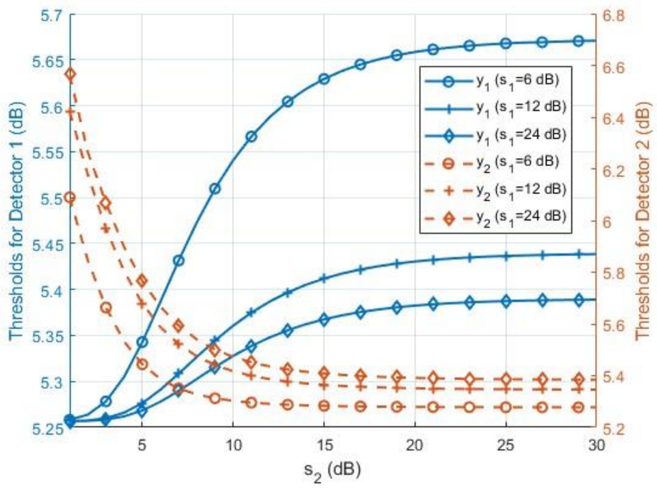

Figure 2. *Result of optimizing the local detection thresholds for the OR rule.*

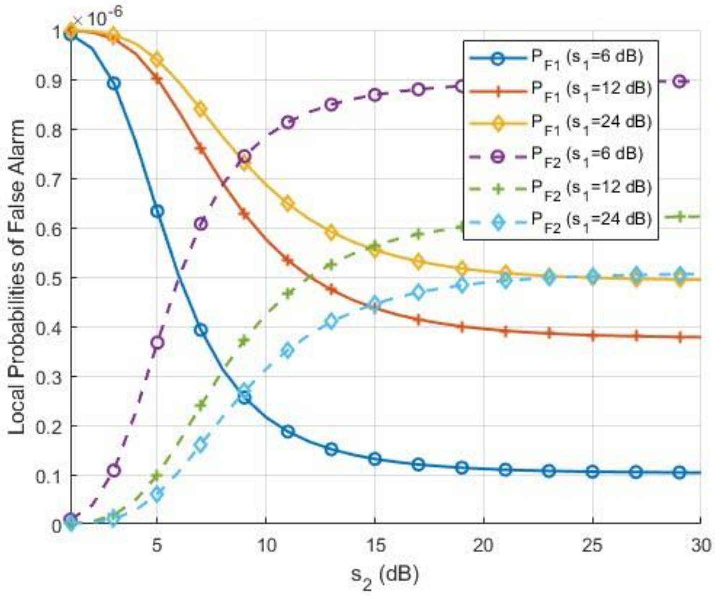

Figure 3. *Result of optimizing the local false alarm probabilities for the OR rule.*

Instead of curves characterizing the performance of target detection in monostatic radars, figures 4 and 5 show slices characterizing the performance of target detection in a multistatic radar system consisting of two local stations using optimized thresholds. Figure 4 shows the performance characteristics of the OR rule, and the performance of the AND rule is represented in figure 5. For the OR rule, the overall detection performance depends on both SCR values of stations. With the AND rule, when the SCRs of two local stations have different values, the overall detection performance depends only on the station with the larger SCR. This means that the system's detection performance under the AND rule is equivalent to that of a station with a larger SCR. It is easy to see that the OR rule is always optimal when comparing the results shown in figures 4 and 5.

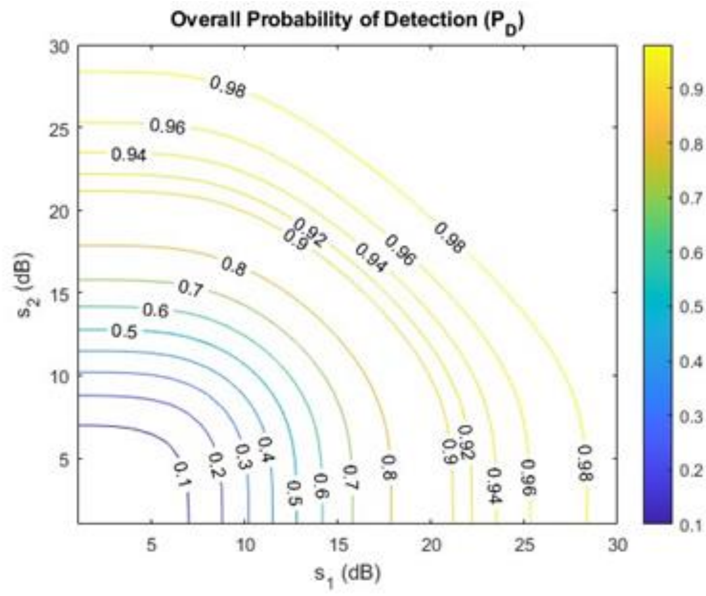

Figure 4. *Performance characteristics of target detection for OR-rule.*

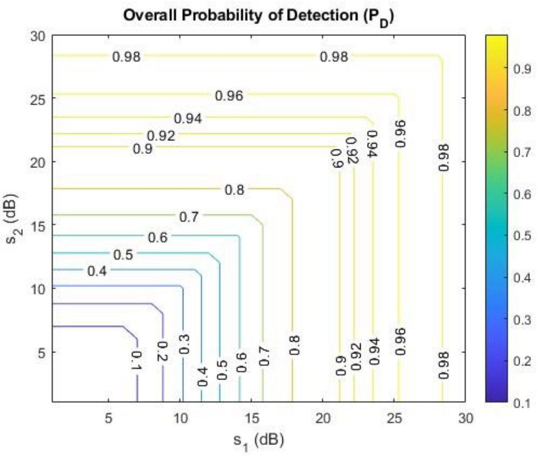

Figure 5. *Performance characteristics of target detection for AND-rule.*

To evaluate the suboptimality of using homogeneous thresholds, figure 6 shows the performance loss (probability) of target detection compared with the optimal thresholding (OR rule). The overall detection probability showed the largest decrease of about 1.6% when one of the two stations had an ambient SCR of 12 dB, while the other station had a low SCR. The detection probability was less decreased in other SCR regions. In particular, for large SCRs, the system's detection performance depends insignificantly on optimizing the local thresholds. In other words, in these regions, a homogeneous threshold can be used without significantly affecting the overall detection performance. The above observations are for target detection in Gaussian clutter, and they should be further investigated in other cases.

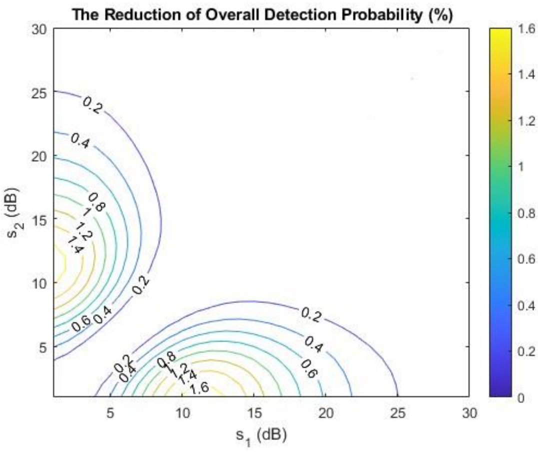

Figure 6. *Comparison of detection performances between optimal and suboptimal thresholds.*

5. CONCLUSIONS

In this study, we use the PSO algorithm to optimize the distributed detection thresholds of multistatic radar systems with parallel configurations. The local threshold levels are optimized according to the Neyman-Pearson criterion for each fusion rule, and then the optimal rule is selected. Simulations were performed using a system of two distributed stations that jointly detect targets without fluctuations against a background of statistically independent Gaussian clutter. The results demonstrate that for the target detection in Gaussian clutter, the OR rule is always optimal. In addition, the optimal threshold of the local station with a large SCR should be reduced, and the threshold of the station with a small SCR should be increased to maintain the given overall false alarm probability. The results also show the advantage of a multistatic radar system compared to monostatic radars when the target detection performance of the optimal fusion rule is still guaranteed even though the SCR of the stations decreases. The advantage of optimizing local thresholds was also analyzed, and it was demonstrated that detection performance was reduced by up to 1.6% in certain SCR regions, while optimizing thresholds in high SCR regions could be omitted when detecting targets in Gaussian clutter. The purpose of this paper is to present a distributed detection threshold optimization method based on PSO to investigate the target detection characteristics of a system with each fusion rule. However, the standard PSO algorithm exhibits slow convergence in the refined search stage and weak performance in problems with many dimensions. In the future, we will focus on overcoming these limitations and compare the proposed method to other local threshold optimization approaches.

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TÓM TẮT

Tối ưu ngưỡng phát hiện phân tán cho hệ thống ra đa nhiều vị trí

Trong bài báo này, chúng tôi đề xuất một phương pháp để tối ưu ngưỡng phát hiện phân tán cho hệ thống ra đa nhiều vị trí. Dưới tiêu chuẩn Neyman-Pearson, ngưỡng phát hiện thành phần được tối ưu sử dụng thuật toán tối ưu bầy đàn (PSO). Các mức ngưỡng thành phần được tối ưu để cực đại xác suất phát hiện tổng thể dưới sự ràng buộc của xác suất báo động lầm tổng thể cho trước. Ưu điểm của PSO là tính đơn giản, ít tham số và tìm kiếm toàn cục hiệu quả. Ví dụ mô phỏng số được đưa ra đối với trường hợp hệ thống ra đa gồm 2 trạm thành phần phát hiện phân tán đối với mục tiêu trong nhiễu Gauss độc lập thống kê. Các kết quả chỉ ra rằng, quy tắc hợp nhất OR luôn tối ưu và mức ngưỡng được xác định linh hoạt cho phép duy trì chất lượng phát hiện tổng thể khi có sự thay đổi không đồng nhất của tỉ số tín/nhiễu (SCR) ở mỗi trạm thành phần. Trong một số trường hợp, có thể bỏ qua việc tối ưu ngưỡng thành phần mà chất lượng phát hiện toàn hệ thống giảm không đáng kể.

Từ khóa: Ra đa nhiều vị trí; Phát hiện phân tán; Tối ưu hóa bầy đàn (PSO).