



## Article

# A Parameter Estimation-Based Anti-Deception Jamming Method for RIS-Aided Single-Station Radar

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**Abstract:** Multi-station radar can provide better performance against deception jamming, but the harsh detection requirements and risk of network destruction undermine the practicability of the multi-station radar. Therefore, it is necessary to further explore the anti-deception jamming performance of a single-station radar. This paper introduces a novel method, based on parameter estimation with a virtual multi-station system, to discriminate range deceptive jamming. The system consists of a single-station radar assisted by the reconfigurable intelligent surfaces (RIS). A unified parameter estimation model for true and false targets is established, and the convex optimization method is applied to estimate the target location and deception range. The Cramer–Rao lower bound (CRLB) of the target localization and the measured deception range is then derived. By using the measured deception range and its CRLB, an optimal discrimination algorithm in accordance with the Neyman–Pearson lemma is designed. Simulation results demonstrate the feasibility of the proposed method and analyze the effects of factors such as signal-to-noise ratio (SNR), deception range, jammer location, and the RISs station arrangement on the discrimination performance.

**Keywords:** reconfigurable intelligent surface (RIS); deception jamming; radar anti-jamming; parameter estimation



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## 1. Introduction

Since the Second World War, radar technology has been developed in an all-round way, and its application scenarios have been extended to meteorological monitoring, target imaging, resource surveying and other fields [1–6]. And the application of radar military field is still the top priority. Radar jamming and anti-jamming technology are promoting the development of each other. With the rapid development of modern electronic warfare (EW), various types of interference are continuously being combined and applied. Radar, as an important detection method for obtaining information, is greatly limited in its operational efficiency under complex electromagnetic conditions [7,8]. To achieve target detection, the research focus in the radar field has shifted towards multi-station radar cooperative detection technology [9–11]. A multi-station radar system consists of multiple spatially distributed transmitting stations, receiving stations, or transceiver stations. This system links multiple radars together through communication means and centrally processes all the information from the targets in each sensor at the system fusion center [12]. Based on this definition of a multi-station radar system, the currently widely studied types of multi-station radar systems include networked radar [13,14], multi-base radar [15,16], and distributed multiple-input multiple-output (MIMO) radar [17–19]. In a multi-station radar system, each radar station can have different systems, frequency bands, and data rates, and they can independently complete the measurement and tracking processes, sharing only the target information at the system fusion center.

Multi-station radar collaboration can also effectively improve anti-jamming capabilities by using multi-view detection and information fusion processing, which has been proven to have more significant advantages than single-station radar [11,20–22]. However, in actual scenarios, the required detection conditions are relatively harsh, and the risk of radar network destruction is inevitable. So, it is still necessary to explore the anti-jamming ability of single-station radar. Reconfigurable intelligent surfaces (RIS), which are widely used in wireless communications, can reconfigure the signal propagation environment and construct distributed detection conditions. It provides a new solution for single-station radar anti-jamming.

RIS, first proposed and validated by CUI et al. in 2014, adopts the idea of binary digital coding to characterize metamaterials, and controls electromagnetic waves by changing the spatial arrangement of “0” and “1” digital coding units [23]. It can be flexibly placed in indoor and outdoor scenarios. Each reflective unit can control the incident signal, and the parameters that can be changed include phase, amplitude, frequency, and even the direction of polarization. The most discussed and practicable one is to change the phase. As a new type of artificially tunable reflector array, each reflector unit of the RIS can independently control the phase and/or amplitude of the reflected signal. The RIS can reconstruct the channel between the transmitting station and the receiving station by skillfully adjusting the phase and amplitude response of each unit, thus providing reconfigurable services with low energy consumption and adaptive communication environment [24]. It is considered to be one of the key technologies to promote future wireless communication systems, especially 6G and subsequent networks [25,26]. In recent years, it has received wide attention in the field of next-generation mobile communication and sensor systems [24,25,27–30], and has been widely used in the field of wireless communication. Many methods have been proposed to improve the performance of communication systems by combining the RIS with traditional communication technologies [31–36]. For example, [31–33] introduced the RIS into MIMO communication systems to improve system performance. RIS-assisted UAV secure communication is discussed in [34]. Refs. [35,36] studied the application of the RIS in uplink and downlink communications, respectively. Refs. [37–39] studied the RIS phase shift and multi-parameter joint optimization algorithm. In [40–42], the RISs were used to improve the direction of arrival (DOA) estimation performance. In addition, the RIS-assisted dual-function radar communication system has also been studied [43–46].

Due to the excellent feature of adjusting channel parameters and its great potential in localization [47–49], the RIS has attracted wide attention in the field of radar research. In the field of radar target detection, Buzzi et al. proposed for the first time the use of the RIS auxiliary radar for target detection [50], Lu et al. used the RIS to improve the detection performance of MIMO radar [51], and [52,53] studied how introducing the RIS into the radar system can effectively improve the radar detection performance in non-line-of-sight (N-LoS) scenarios. In the field of radar localization, Zou et al. built a dual RIS-assisted radar system to achieve centimeter-level location measurement accuracy and decimeter-level speed measurement accuracy [54]. Ref. [55] used the RIS to solve the joint localization and synchronization problems of mobile stations in millimeter wave multiple-input-single-output (MISO) system. RIS is introduced to a 2D radar to realize target three-dimensional localization [56]. Ref. [57] proves that the RIS-assisted radar system is more robust to target obstruction than the conventional radar systems.

However, to the best of our knowledge, there are relatively few studies on how to use the RIS for radar anti-range deception jamming. Inspired by [58], this paper proposes a novel method to resist deceptive jamming based on parameter estimation. The RIS is used to construct a virtual multi-station radar system, enabling a single-station radar to obtain multi-view spatial diversity gain. Then, based on the measurement information equation of the RIS-assisted radar system, the convex optimization method is applied to estimate the target location and deception range. And the corresponding Cramer–Rao lower bound (CRLB) is derived. Finally, the estimated value of the deceptive range parameter and its



The target echo signal that the radar receives is the overlapping signal of the echo signals from both the direct channel and all RIS reflection channels. As a result, a target will manifest  $M + 1$  times within the radar echo, leading to  $M + 1$  distinct measurements. For discriminating the measurement channel corresponding to each radar-acquired measurement, a specific coding sequence is designed for each RIS [56].

The target echo  $r(t)$  received by the radar is divided into two parts, namely

$$r(t) = r_{dir}(t) + r_{aux}(t), \quad (1)$$

where  $r_{dir}(t) = \alpha s(t - t_d - t_{\Delta d}) + w_{dir}(t)$  is the echo signal in the direct channel,  $\alpha$  represents the amplitude of the target,  $s(t)$  is the transmitted signal of the radar,  $t_d = 2d_T/c$  refers to the time delay,  $d_T = \|\mathbf{q} - \mathbf{q}_r\|$  represents the range between the target or the jammer and the radar,  $t_{\Delta d} = 2\Delta d/c$  is the time delay caused by deception jamming,  $c$  is the speed of light, and  $w_{dir}(t)$  is the noise following a Gaussian distribution. When the deception range  $\Delta d = 0$ , the received echo signal is the true target echo signal. In this way, the signal model is valid for both true and false targets with different values of  $\Delta d$ , which is the reason that the deception range  $\Delta d$  can be used to discriminate true and false targets.

In the direct channel, the measured range, azimuth, and elevation of the target are  $d$ ,  $\theta$  and  $\varphi$ , respectively, which can be expressed as

$$d = d_T + \Delta d + n_d, \quad (2)$$

$$\theta = \arctan\left(\frac{y - y_r}{x - x_r}\right) + n_\theta, \quad (3)$$

$$\varphi = \arccos\left(\frac{z - z_r}{d_T}\right) + n_\varphi, \quad (4)$$

where  $\|\bullet\|$  represents the Euclidean norm.  $n_d$ ,  $n_\theta$  and  $n_\varphi$  are, respectively, the measurement noise of range, azimuth, and pitch angle, which obey normal distribution. Namely,  $n_d \sim N(0, \sigma_d^2)$ ,  $n_\theta \sim N(0, \sigma_\theta^2)$ ,  $n_\varphi \sim N(0, \sigma_\varphi^2)$ . The  $\sigma_d$ ,  $\sigma_\theta$ , and  $\sigma_\varphi$ , respectively, represent the measurement errors in radar range, azimuth, and pitch determined by the signal-to-noise ratio (SNR) of the target. The relational equation is given by [59],

$$\sigma_d = \frac{1.4c}{B\sqrt{SNR_{dir}}}, \quad (5)$$

$$\sigma_\theta = \frac{\theta_{3dB}}{1.6\sqrt{2SNR_{dir}}}, \quad (6)$$

$$\sigma_\varphi = \frac{\theta_{3dB}}{1.6\sqrt{2SNR_{dir}}}, \quad (7)$$

where  $B$  is the bandwidth,  $\theta_{3dB}$  is the 3dB beamwidth, and  $SNR_{dir}$  is the target SNR in the direct channel.

$r_{aux}(t) = \sum_{m=1}^M r_m(t)$  is the target echo signal of the auxiliary channels,  $r_m(t)$  is the echo signal received by the  $m$ -th auxiliary channel,

$$r_m(t) = \sum_{l=1}^L \alpha_{m,l} e^{j(\psi_{t,l} + \phi_l^m + \psi_{r,l})} s(t - t_m) + w_m(t), \quad (8)$$

where  $l = 1, 2, \dots, L$ ,  $L$  is the number of subwavelength size surface elements of the RIS.  $\alpha_{m,l}$  is the target amplitude of the  $l$ -th element from the  $m$ -th RIS.  $\psi_{t,l}$  and  $\psi_{r,l}$  are the target phases of the target-RIS and RIS-radar channels, respectively.  $\phi_l^m$  is the adjustable phase of the  $l$ -th reflector of the  $m$ -th RIS. When  $\phi_l = -\psi_{t,l} - \psi_{r,l}$ , the resolution unit under test reaches the highest SNR [56].  $t_m = (d_T + d_{T,m} + d_{R,m})/c$  refers to the time delay in the RIS auxiliary channel,  $d_{T,m} = \|\mathbf{q} - \mathbf{q}_{R,m}\|$  is the range between the target and the  $m$ -th RIS, and

$d_{R,m} = \|\mathbf{q}_r - \mathbf{q}_{R,m}\|$  is the range between the radar and the  $m$ -th RIS. Gaussian noise  $w_m(t)$  is independent of  $w_{dir}(t)$ .

In the auxiliary channel, since the range between the radar and the RIS is known, the sum of the measured range  $d_m$  represent the total range from the radar to the target and then to the  $m$ -th RIS, which can be expressed as

$$d_m = d_T + d_{T,m} + 2\Delta d + n_{d,m}, \quad (9)$$

where  $n_{d,m} \sim N(0, \sigma_{d,m}^2)$  represents the measurement noise,  $\sigma_{d,m} = 1.4c / (B\sqrt{SNR_m})$  represents the ranging error.  $SNR_m$  refers to the target SNR in the  $m$ -th auxiliary channel, and its relationship with the SNR of the direct channel can be written as

$$(SNR_m)_{dB} = 10\lg(d_T^2 / (d_{T,m} + d_{R,m})^2) + (SNR_{dir})_{dB}. \quad (10)$$

Define the parameters to be measured of the radar direct channel and auxiliary channels as a vector  $\mathbf{Z} = [d, \theta, \varphi, d_1, \dots, d_M]^T$ , then the target measurement equation can be expressed as

$$\mathbf{Z} = \begin{bmatrix} d \\ \theta \\ \varphi \\ d_1 \\ \vdots \\ d_M \end{bmatrix} = \begin{bmatrix} h_1(\mathbf{X}) \\ h_2(\mathbf{X}) \\ h_3(\mathbf{X}) \\ h_4(\mathbf{X}) \\ \vdots \\ h_{M+3}(\mathbf{X}) \end{bmatrix} + w, \quad (11)$$

from Equations (2)–(4) and (9), it follows that

$$h_1(\mathbf{X}) = d_T + \Delta d, \quad (12)$$

$$h_2(\mathbf{X}) = \arctan \frac{y - y_r}{x - x_r}, \quad (13)$$

$$h_3(\mathbf{X}) = \arccos \left( \frac{z - z_r}{d_T} \right), \quad (14)$$

$$h_i(\mathbf{X}) = d_T + d_{T,i-3} + 2\Delta d, 4 \leq i \leq M+3, \quad (15)$$

$$w = [\sigma_d^2, \sigma_\theta^2, \sigma_\varphi^2, \sigma_{d,1}^2, \dots, \sigma_{d,M}^2]^T. \quad (16)$$

Then, the anti-deception jamming problem involves discriminating true and false targets based on the measurement vector  $\mathbf{Z}$  in the virtual multi-station radar system, which is realized by the deception range estimation along with the target localization.

### 3. Deception Parameter Estimates

#### 3.1. Deception Parameter Estimation Method

In this section, the measured values  $r, \theta$ , and  $\varphi$  of the direct channel are combined with the measured values  $d_m, m = 1, 2, \dots, M$  in the auxiliary channels to estimate the target location and deception range. When target localization and deception range estimation are implemented,  $\hat{\mathbf{q}} = (\hat{x}, \hat{y}, \hat{z})$  is the estimated coordinate value of the target in the Cartesian coordinate system, and  $\Delta\hat{d}$  is the estimated value of the deception range. Using the measured value of the radar range in the direct channel and the measured value of the radar range in the auxiliary channel, the objective function of the system can be referred to

$$F(\hat{x}, \hat{y}, \hat{z}, \Delta\hat{d}) = \left( r - \Delta\hat{d} - R_{T \rightarrow r} \right)^2 + \sum_{m=1}^M \left( d_m - 2\Delta\hat{d} - R_{T \rightarrow \text{RIS},m} - R_{T \rightarrow r} \right)^2 \quad (17)$$

where  $R_{T \rightarrow r} = \|\hat{\mathbf{q}} - \mathbf{q}_r\|$ ,  $R_{T \rightarrow \text{RIS},m} = \|\hat{\mathbf{q}} - \mathbf{q}_{R,m}\|$ .

Further considering the measured target azimuth angle  $\theta$  and elevation angle  $\varphi$ , the following constraints can be obtained,

$$\theta - \Delta\theta < \arctan\left(\frac{\hat{y} - y_r}{\hat{x} - x_r}\right) < \theta + \Delta\theta, \quad (18)$$

$$\varphi - \Delta\varphi < \arccos\left(\frac{\hat{z} - z_r}{R_{T \rightarrow r}}\right) < \varphi + \Delta\varphi, \quad (19)$$

where  $\Delta\theta$  and  $\Delta\varphi$  are, respectively, determined by the radar azimuth and elevation angle measurement errors. Set the confidence interval to 99.7% according to the three-sigma rule, then  $\Delta\theta = 3\sigma_\theta$ ,  $\Delta\varphi = 3\sigma_\varphi$ .

Therefore, the estimation of target location and deception range can be modeled as the following optimization problem,

$$\begin{aligned} \min_{(\hat{x}, \hat{y}, \hat{z}) \in \Omega} \quad & F(\hat{x}, \hat{y}, \hat{z}, \Delta\hat{d}), \\ \text{s. t.} \quad & \theta - \Delta\theta < \arctan\left(\frac{\hat{y} - y_r}{\hat{x} - x_r}\right) < \theta + \Delta\theta, \\ & \varphi - \Delta\varphi < \arccos\left(\frac{\hat{z} - z_r}{R_{T \rightarrow r}}\right) < \varphi + \Delta\varphi. \end{aligned} \quad (20)$$

where  $\Omega$  represents the three-dimensional space in which the target may exist.

Next, it is proved that the optimization problem (20) is convex, and then the convex optimization method is used to find the minimum value of its estimated parameter  $(\hat{x}, \hat{y}, \hat{z}, \Delta\hat{d})$ .

First, it is proved that the optimization function  $F(\hat{x}, \hat{y}, \hat{z}, \Delta\hat{d})$  is convex.  $R_{T \rightarrow R}$  and  $R_{T \rightarrow RIS, m}$  are the square root of the Euclidean range, so they are both convex functions about  $(\hat{x}, \hat{y}, \hat{z})$ . As shown in (17),  $F(\hat{x}, \hat{y}, \hat{z}, \Delta\hat{d})$  is the sum of several square terms, and each square term is a convex function. Therefore,  $F(\hat{x}, \hat{y}, \hat{z}, \Delta\hat{d})$  is also a convex function.

Second, it is proved that the constraints shown in (18) are convex sets. (18) shows that the target is in a sector-shaped area, where the measured azimuth angle  $\theta$  is the central angle and the incremental angle around  $\theta$  is  $\Delta\theta$ . For any linear combination of any two points  $A = (x_1, y_1, z_1)$  and  $B = (x_2, y_2, z_2)$  in the sector area, a new point with coordinates  $(\lambda x_1 + (1 - \lambda)x_2, \lambda y_1 + (1 - \lambda)y_2, \lambda z_1 + (1 - \lambda)z_2)$  will be generated. Since  $\lambda$  and  $(1 - \lambda)$  are non-negative, according to the properties of the arctangent function, it can be concluded that the arctangent value of this new point will also be between  $\theta - \Delta\theta$  and  $\theta + \Delta\theta$ . Therefore, based on the definition of convex sets in geometry, this set is convex.

Finally, by the same token, it can be proved that (19) is also a convex set.

For the convex optimization problem (20), the interior point method (IPM) is used here. Compared with other optimization algorithms, the IPM offers numerous advantages for constrained optimization problems. It is less sensitive to the selection of the initial point and can effectively avoid getting trapped in local minima.

### 3.2. CRLB

CRLB is the lower bound of the root mean square error of any unbiased estimator in estimating location parameters. For the location parameter vector  $\theta$  and the corresponding unbiased estimator  $\hat{\theta}$ , it satisfies

$$E[(\hat{\theta} - \theta)(\hat{\theta} - \theta)^H] \geq J_\theta^{-1}, \quad (21)$$

where  $E[\bullet]$  represents the expectation,  $J_\theta$  is the Fisher information matrix (FIM), and its  $(i, j)$ -th element is

$$[J_\theta]_{ij} \triangleq -E\left[\frac{\partial \ln p(x|\theta)}{\partial \theta_i} \frac{\partial \ln p(x|\theta)}{\partial \theta_j}\right], \quad (22)$$

where  $p(x|\theta)$  is the likelihood function of random variable  $x$  under condition  $\theta$ . The inverse of FIM,  $J_\theta^{-1}$ , is the CRLB matrix of  $\theta$ .

In the Gaussian observation scenario  $x \sim N(\mu(\theta), R(\theta))$ , then the FIM of  $\theta$  is given by the following formula [60],

$$[J_\theta]_{ij} = \left[ \frac{\partial \mu(\theta)}{\partial \theta_i} \right]^T R^{-1}(\theta) \left[ \frac{\partial \mu(\theta)}{\partial \theta_j} \right] + \frac{1}{2} \text{tr} \left[ R^{-1}(\theta) \frac{\partial R(\theta)}{\partial \theta_i} R^{-1}(\theta) \frac{\partial R(\theta)}{\partial \theta_j} \right]. \quad (23)$$

$M$  RISs-assisted radar detects one target. The target carries a self-defense jammer to deceive the radar. The deception range is  $\Delta d$  and the target's location is  $[x, y, z]$ . Define the parameters to be estimated as vectors  $X = [x, y, z, \Delta d]^T \triangleq [x_1, x_2, x_3, x_4]^T$ , let  $H(X) = [h_1(X), h_2(X), \dots, h_{M+3}(X)]^T$ , the Equation (11) can be written as

$$Z = H(X) + w. \quad (24)$$

At this time,  $Z \sim N(H(X), R(X))$ ,  $R(X) = wI$ , according to (23), and the FIM of parameter  $X$  whose variance has nothing to do with the estimated parameters can be simplified to

$$[J_X]_{ij} = \left[ \frac{\partial H(X)}{\partial X_i} \right]^T R^{-1}(X) \left[ \frac{\partial H(X)}{\partial X_j} \right] = \sum_{n=1}^{M+3} \frac{1}{\sigma_n^2} \frac{\partial h_n}{\partial x_i} \frac{\partial h_n}{\partial x_j}. \quad (25)$$

Therefore, the CRLB matrix of  $X$  is  $C_X = J_X^{-1} \triangleq [c_{ab}]_{4 \times 4}$ , among them, the main diagonal elements of  $C_X$  are, respectively, the CRLB of  $x, y, z$  and  $\Delta d$ , namely

$$\sigma_x^2 = c_{11}, \quad \sigma_y^2 = c_{22}, \quad \sigma_z^2 = c_{33}, \quad (26)$$

$$\sigma_{\Delta d}^2 = c_{44}. \quad (27)$$

Respectively, the CRLB of the standard deviation of target localization and the deception range are  $\sigma_o = \sqrt{\sigma_x^2 + \sigma_y^2 + \sigma_z^2}$  and  $\sigma_{\Delta d}$ .

CRLB is a theoretical limit to measure the accuracy of an estimation, which gives the minimum theoretical value of the estimation error considering all possible observations and target parameter estimation methods. This is a crucial performance indicator that reveals the optimal performance achievable based on the observed values. When RIS assists radar to detect targets, the actual performance of the system can be understood more comprehensively by studying the CRLB of radar localization and deception range. This knowledge can be used to further optimize the system design and enhance the overall performance of the radar system.

Next, the performance of the proposed parameter estimation algorithm will be evaluated through simulation experiments, geometric dilution of precision (GDOP) is simulated to compared with the CRLB. The GDOP is a measure of the quality of target localization [61]. The lower the GDOP value, the more accurate the location estimation. A high GDOP value means that the accuracy of the location estimate is reduced, and therefore the position uncertainty is increased. Assume that the virtual multi-station radar consists of two RISs and one radar. The coordinate of the radar is  $[0, 0, 0]$  km, the coordinate of the first RIS is  $[40, 0, 0]$  km, and the coordinate of the second RIS is  $[-40, 0, 0]$  km. The forwarding jammer as a target is located at  $[20, 40, 12]$  km and generates active false targets with a deception range of 2 km.

Figure 2 illustrates the variation in the GDOP with SNR, while Figure 3 depicts the variation in the mean square error (MSE) of the deception range measurements with SNR. The parameter estimation method achieves the optimal solution through convex optimization and conducts  $10^4$  Monte Carlo simulation experiments for each SNR value. The statistical average is then used to determine the estimation accuracy. As observed from Figures 2 and 3, the parameter estimation method exhibits a nearly unbiased estimation accuracy. Furthermore, under high SNR conditions, the GDOP and MSE approaches

the limit of the CRLB. This demonstrates that the CRLB provides a sufficiently tight performance lower bound for the proposed estimation method and can be accurately utilized to describe its estimation accuracy.

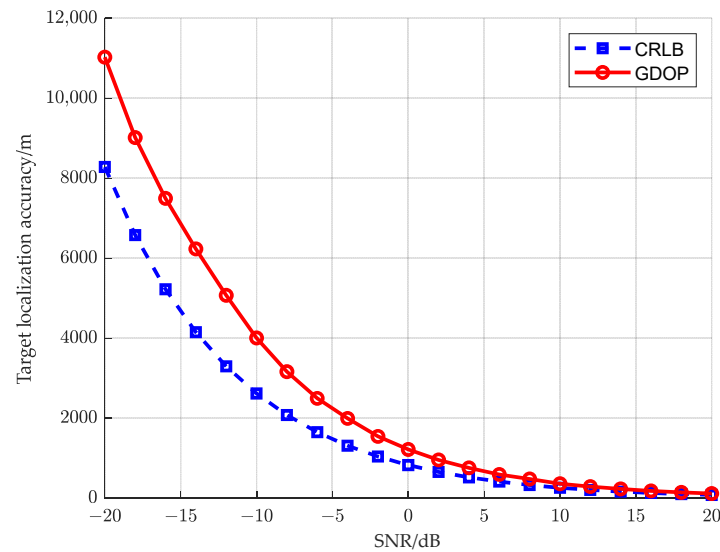


**Figure 2.** Target localization accuracy.

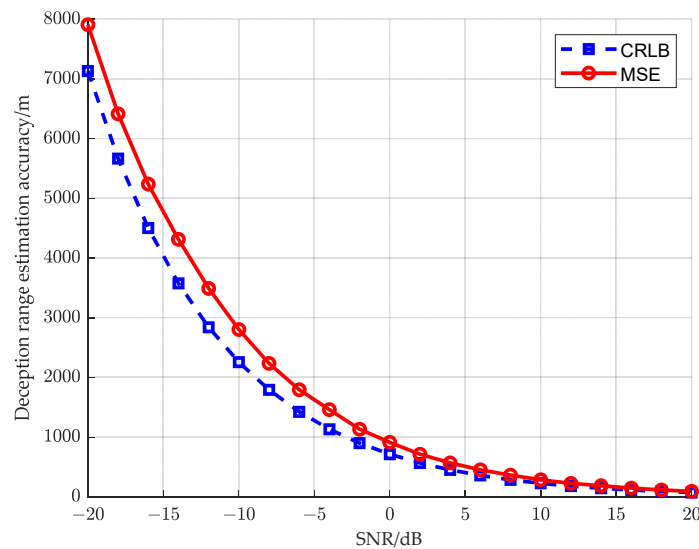


**Figure 3.** Deception range estimation accuracy.

#### 4. Active False Target Discrimination

Using the estimated value  $\Delta\hat{d}$  and CRLB in (27), the optimal discriminator can be designed to discriminate true and false targets. The target discrimination problem can be modeled as a hypothesis testing problem, which contains two hypotheses: null hypothesis ( $H_0 : \Delta d = 0$ ) and its alternative hypothesis ( $H_1 : \Delta d \neq 0$ ). Under the null hypothesis, the detected target is a true target; under the alternative hypothesis, it is an active false target generated by forwarding jammers. Due to the existence of estimation error, the estimated value of deception range  $\Delta\hat{d}$  is regarded as a random variable, namely,  $\Delta\hat{d} \sim N(\Delta d, \sigma_{\Delta d}^2)$ . According to the Neyman–Pearson criterion, the optimal discriminator is

$$\frac{\Delta\hat{d}^2}{\sigma_{\Delta d}^2} \underset{H_1}{\overset{H_0}{\leq}} \eta. \quad (28)$$

If the discrimination statistic exceeds the discrimination threshold  $\eta$ , the target is discriminated as an active false target, otherwise, it is discriminated as a true target. The distribution function of the discriminant statistic under  $H_0$  and  $H_1$  is

$$\begin{cases} H_0 : \Delta d^2 / \sigma_{\Delta d}^2 \sim \chi_1^2 \\ H_1 : \Delta d^2 / \sigma_{\Delta d}^2 \sim \chi_1^2(\Delta d^2 / \sigma_{\Delta d}^2) \end{cases}, \quad (29)$$

where  $\chi_1^2$  is the chi-square distribution with 1 degree of freedom,  $\chi_1^2(\Delta d^2 / \sigma_{\Delta d}^2)$  is the non-central chi-square distribution with 1 degree of freedom, and the non-central parameter is  $\Delta d^2 / \sigma_{\Delta d}^2$  [62].

The false target is discriminated on the premise that the expected true target discrimination probability  $P_{PT} = P\{H_0|H_0\}$  is definite. According to (29), the discrimination threshold can be obtained as  $\eta = F_{\chi_1^2}^{-1}(P_{PT})$ . The theoretical discrimination probability of active false targets is

$$P\{H_1|H_1\} = 1 - F_{\chi_1^2(\Delta d^2 / \sigma_{\Delta d}^2)}(\eta), \quad (30)$$

where  $F_{\chi_1^2}^{-1}(\bullet)$  is the inverse cumulative distribution function of  $\chi_1^2$ , and  $F_{\chi_1^2(\Delta d^2 / \sigma_{\Delta d}^2)}(\bullet)$  is the cumulative distribution function of  $\chi_1^2(\Delta d^2 / \sigma_{\Delta d}^2)$ .

## 5. Numerical Experiments

Based on the above model, a virtual multi-station radar system was built, and a simulation experiment was conducted on the active false target discrimination algorithm. The simulated parameters are the same as that in Section 3.2. An expected true target discrimination probability  $P_{PT} = 99.9\%$  was preset in the experiment.

First, the simulation is conducted to determine the active false target discrimination probability  $P_{FT}$  under different configurations of SNR and deception range. The performance of the proposed method is then compared with an existing data fusion based false target discrimination method in [58], and the difference is that only the range measurements of auxiliary channels are used here to ensure that it is in the same scenario as the proposed algorithm. Next, the performance of the proposed discrimination algorithm is discussed when the jammer is placed in different spatial locations. Furthermore, the impact on discrimination performance of the virtual multi-station radar system under different layout schemes was evaluated. Finally, the effect of radar-to-RIS distance on performance is discussed, and the simulation gives the maximum distance threshold for the proposed method.

### 5.1. Simulation Analysis of Active False Target Discrimination Probability

Figure 4 depicts the trend of active false target discrimination probability changing with SNR. The multiple curves in the figure represent simulation results at different deception ranges  $\Delta d$ , specifically the case of  $\Delta d = 1$  km, 2 km, 3 km. The simulation results indicate that with an increase in SNR or deception range, the probability of effectively discriminating active false targets also increases. This can be attributed to the fact that higher SNR enhances estimation accuracy, making the proposed discrimination algorithm more sensitive to variations in deception range under higher SNR conditions. Additionally, a larger deception range strengthens the differentiation between true and false targets, thereby enhancing the likelihood of successfully discriminating false targets. As shown in Figure 4, based on comparing the probabilities of different methods, under the same  $\Delta d$  conditions, the discrimination probabilities of the proposed method are all higher than the existing method [58]. Under the conditions of  $\Delta d = 3$  km and SNR = 10 dB, the existing methods improve the discrimination probability up to 90%. Simulation experiments show the advantage of the proposed method over existing data fusion-based method in terms of target discrimination probability.

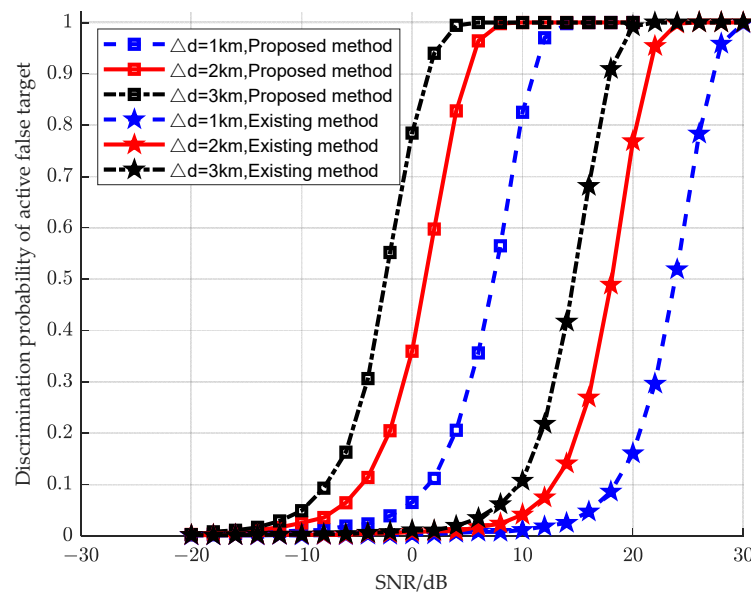


**Figure 4.** Active false target discrimination probability.

### 5.2. Analysis of the Influence of Jammer Location

The possible location area of the jammer is set to  $[-50, 5, 12] * [50, 80, 12]$  km, and it is assumed that the SNR of the direct channel of the jammer at  $[20, 40, 12]$  km is 10 dB. The deception range  $\Delta d$  is 3 km, the location of the first RIS is  $[20, 0, 0]$  km, and the location of the second RIS is  $[-20, 0, 0]$  km. For each location that a jammer may occupy, the CRLB of the deception range estimation is calculated and the results are shown in Figure 5. Then, the proposed discrimination method is applied to discriminate the active false targets generated by the jammer, and the distribution of the discrimination probability is displayed in Figure 6. It can be observed from Figure 5 that as the range from the jammer to the virtual multi-station radar system increases, the estimation accuracy of the deception range gradually decreases, which directly impacts the ability to discriminate false targets. This phenomenon aligns with the changing trend of false target discrimination probability in Figure 6. When the jammer is near to the radar system, the proposed discrimination algorithm can effectively discriminate false targets generated by a smaller deception range.

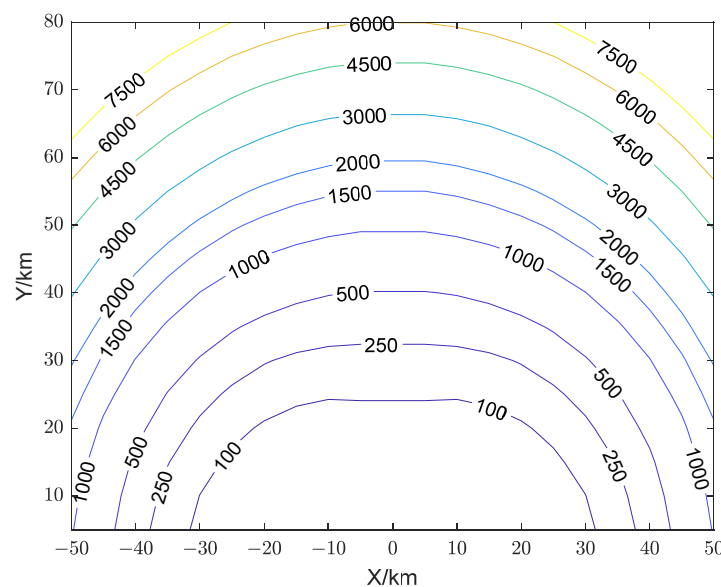


**Figure 5.** Deception range estimation accuracy under different jammer locations.

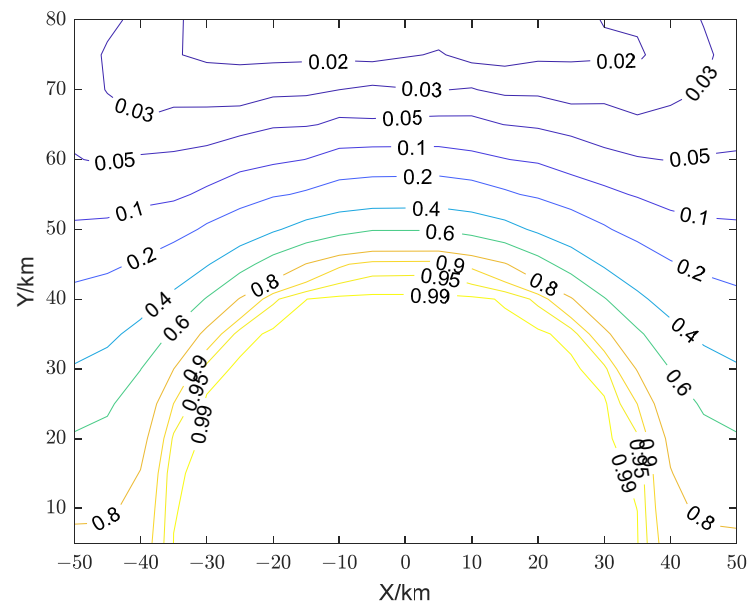


**Figure 6.** Active false target discrimination probability under different jammer locations.

### 5.3. Analysis of the Impact of Multi-RIS Site Deployment

In order to explore the impact of the RISs deployment location in the virtual multi-station radar on the performance of the active false target discrimination algorithm, four different RIS deployment configurations were additionally considered, as shown in Table 1. Among them, the first station layout configuration is consistent with the simulation conditions in Figure 6 and serves as a benchmark comparison experiment. Compared with the first deployment configuration, the range between the RISs and the radar in the second configuration is closer, showing a higher concentration of deployment. The latter two configurations reflect changes in the number of the RISs in the virtual multi-station radars.

**Table 1.** Virtual multi-station radar parameter information table.

| Configuration | Number of the RIS | The RISs Location/km                             |
|---------------|-------------------|--------------------------------------------------|
| 1             | 2                 | [20, 0, 0], [−20, 0, 0]                          |
| 2             | 2                 | [10, 0, 0], [−10, 0, 0]                          |
| 3             | 4                 | [−40, 0, 0], [−20, 0, 0], [20, 0, 0], [40, 0, 0] |
| 4             | 4                 | [−20, 0, 0], [−10, 0, 0], [10, 0, 0], [20, 0, 0] |

Under the different RIS site configuration conditions in Table 1, the active false target discrimination probabilities are obtained, as shown in Figures 6–9.

Comparing Figure 7, Figure 8, and Figure 9 with Figure 6, respectively, it can be observed that the smaller the range between the RISs and the radar, the greater the impact on active false targets, and the worse the discrimination performance. This is because when the RISs is closer to the radar, the difference in viewing angles provided is smaller, leading to a significant reduction in the area where false targets can be better discriminated. Therefore, when the RIS is deployed relatively far away, it can detect targets from more and wider angles, effectively improving the estimation accuracy of the deception range and enhancing the discrimination performance of false targets. This conclusion aligns with the view on optimizing the RIS site deployment mentioned in [58].

Further comparing Figure 6 with Figure 8, it is evident that the greater the number of RISs in the virtual multi-station radar, the better the performance in discriminating false targets, since more RISs allows for more target information to be utilized in estimating the deception range, thereby improving the ability to discriminate active false targets.

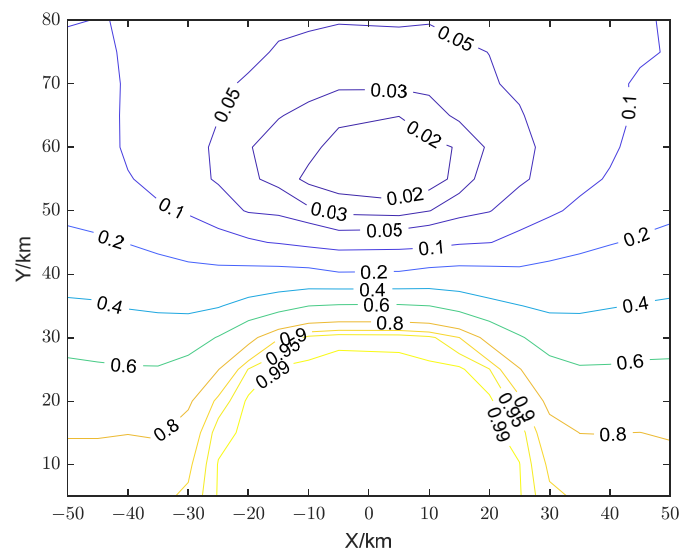


**Figure 7.** Active false target discrimination probability for configuration 2.

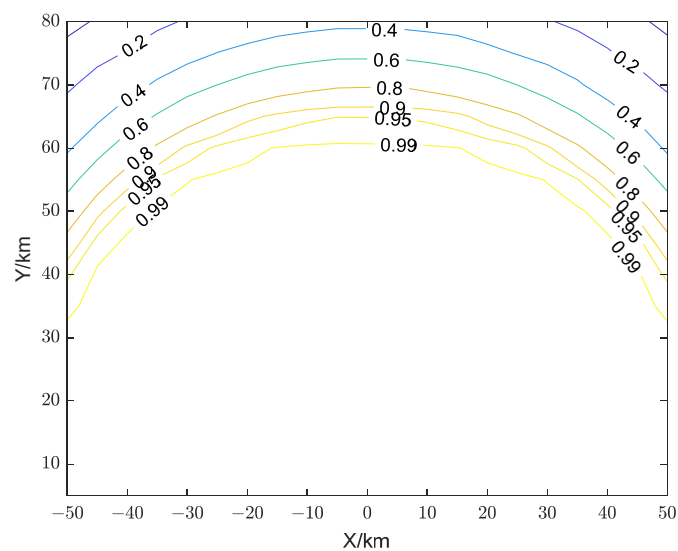


**Figure 8.** Active false target discrimination probability for configuration 3.

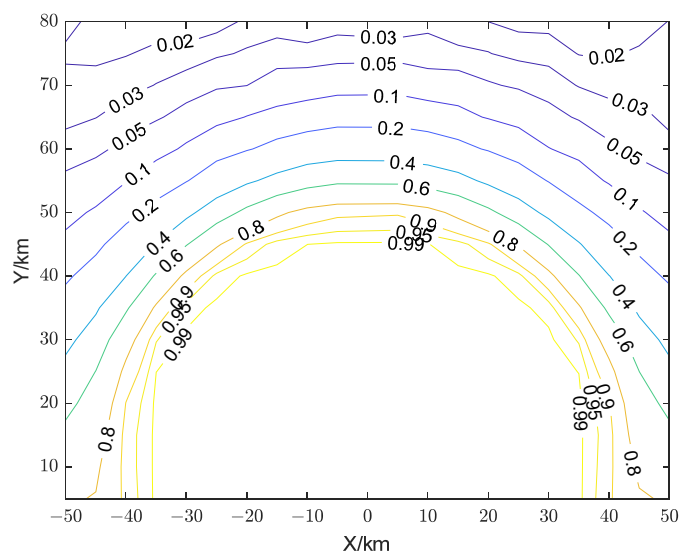


**Figure 9.** Active false target discrimination probability for configuration 4.

#### 5.4. Analysis of the Impact of Distance Between RIS and Radar

As can be seen from the previous section, the distance between the RIS and radar will affect the discrimination probability of the virtual multi-station radar system. The discrimination probability of a virtual multi-station radar system is a complex function of multiple parameters such as SNR, target range, deception range, and the distance from the radar to the RIS. In a fixed scene, the impact of the distance from the radar to the RISs on the discrimination probability can be obtained through numerical simulation.

Assume that the virtual multi-station radar consists of two RISs auxiliary radars. The coordinates of the radar are  $[0, 0, 0]$  km, the coordinates of the RIS1 are  $[d_{Rr}, 0, 0]$  km, and the coordinates of the RIS2 are  $[-d_{Rr}, 0, 0]$  km. The forwarding jammer is located at  $[20, 40, 12]$  km. The SNR is set as 10 dB. The simulation shows the discrimination probability of active false targets varies with the  $d_{Rr}$  under different deception range, specifically the cases of  $\Delta d = 1$  km, 2 km, 3 km.

Figure 10 illustrates the variation in discrimination probability with the distance between the radar and the RISs. As the distance increases, the diversity gains and the discrimination probability also increase. It is assumed that the discrimination performance is considered ineffective, when the discrimination probability falls below 0.8. In the simulated scenario, the threshold distance  $d_{Rr,th}$  corresponding to the three deception ranges are 40 km, 25 km, and 20 km, respectively. When the distance from RIS to radar is lower than the threshold  $d_{Rr,th}$ , the discrimination performance of the virtual multi-station radar system will be less than 0.8. It should be noted that the simulation is performed with a fixed signal-to-noise ratio. The practical situation will be more complex than that. Excessively large  $d_{Rr}$  will cause the SNR to decrease and will also lead to the decrease in the discrimination probability. All these factors need to be considered when laying out the system.

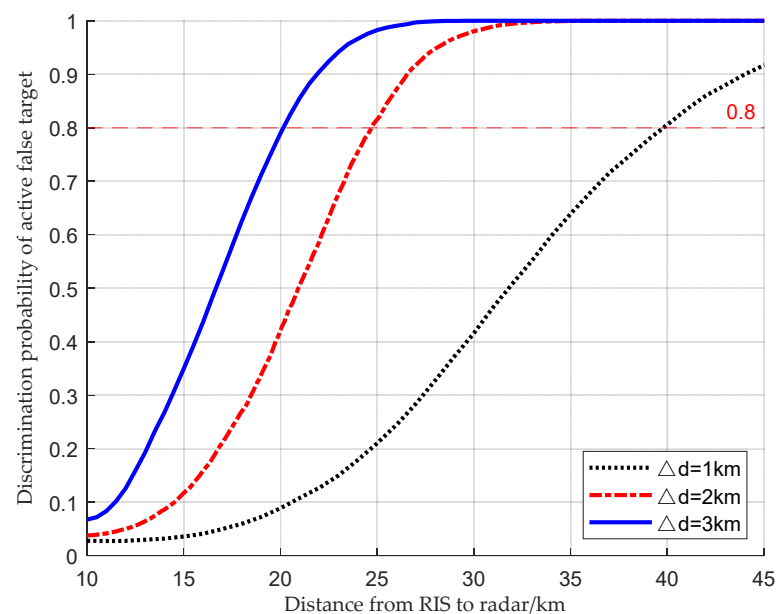


**Figure 10.** Active false target discrimination probability changing with distance from RIS to radar.

## 6. Conclusions

This paper proposes a novel anti-deception jamming method that utilizes the RISs assistance and the parameter estimation. The RISs is integrated into a single-station radar system to leverage its unique characteristics in reconstructing the signal propagation environment. A virtual multi-radar system is established, and a parameter estimation-based approach is employed to discriminate active false targets. Simulation experiments demonstrate that this method can approach the CRLB at higher SNR, confirming the effectiveness of this method. The paper also analyzes the variation pattern of the discrimination proba-

bility of active false targets with respect to the SNR. It is observed that the discrimination probability is sensitive to the deception range, particularly within the 0–5 dB range. Higher deception ranges correspond to higher discrimination probabilities, under the same SNR. Meanwhile, the proposed algorithm is compared with the existing algorithms. Under the same conditions, the proposed algorithm has higher discrimination probability than the algorithm based on data fusion. In addition, the estimation accuracy of the deception range and the discrimination probability of active false targets under different jammer locations are investigated, yielding results consistent with the change in the false target discrimination probability with SNR. Then, the impact of different RIS station locations, the numbers of RISs and the radar-to-RIS distance on the discrimination probability of active false targets is analyzed. Both the number of RISs and the degree of dispersion of the RIS locations affect the discrimination probability. A larger number of the RISs and a larger aperture of the virtual multi-radar result in more diversity gain to improve the discrimination probability. It is worth noting that the method proposed in this paper belongs to data-level processing and may face a high information loss rate. Future research will focus on developing anti-jamming methods that leverage RIS-assisted signal-level processing, in which the target echoes can be directly used for anti-jamming with the amplitude and even phase information.

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