Clutter Suppression for Target Detection Using Hybrid Reconfigurable Intelligent Surfaces

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***Abstract*—Reconfigurable intelligent surface (RIS) technology is a promising approach being considered for future wireless communications due to its ability to control signal propagation with low-cost elements. This paper explores the use of an RIS for clutter mitigation and target detection in radar systems. Unlike conventional reflect-only RIS, which can only adjust the phase of the reflected signal, or active RIS, which can also amplify the reflected signal at the cost of significantly higher complexity, noise, and power consumption, we exploit hybrid RIS that can configure both the phase and modulus of the impinging signal by absorbing part of the signal energy. Such RIS can be considered as a compromise solution between conventional reflect-only and active RIS in terms of complexity, power consumption, and degrees of freedoms (DoFs). We consider two clutter suppression scenarios: with and without knowledge of the target range cell. The RIS design is formulated by minimizing the received clutter echo energy when there is no information regarding the potential target range cell. This turns out to be a convex problem and can be efficiently solved. On the other hand, when target range cell information is available, we maximize the received signal-to-noise-plus-interference ratio (SINR). The resulting non-convex optimization problem is solved through fractional programming algorithms. Numerical results are presented to demonstrate the performance of the proposed hybrid RIS in comparison with conventional RIS in clutter suppression for target detection.**

***Index Terms*—Reconfigurable intelligent surface, target detection, clutter suppression, convex optimization**

I. Introduction

In recent years, reconfigurable intelligent surfaces (RISs) have attracted significant attention in the wireless communication community [1]–[4]. An RIS can configure the wireless environment in a favorable manner by properly tuning the reflection coefficients of the surface's low-cost passive elements. Although RISs were first proposed for communications, they have gained significant attention within the radar community. Specifically, an RIS can be employed to extend the coverage area [5], enhance the system reliability [6], [7], improve parameter estimation performance [8], and suppress the clutter interference [9]. In addition, RISs were recently shown to play an important role for spectrum sharing between radar and communication systems. RISs have been proposed to assist dual-function radar-communication (DFRC) transmission design to provide additional degrees of freedom (DoFs) to improve performance.

By judiciously tuning the phase shifts of the RIS elements, the signals from different paths (e.g., signals re-radiated from the RIS and the direct path from the transmitter to the receiver) can be added either constructively to enhance the received signal power at the desired users, or destructively to suppress the interference to unintended users. With this motivation, the work in [10] and [11] focused on RIS-assisted interference mitigation for radar and communication system co-existence on shared spectrum. Specifically, one RIS is used to suppress the interference from a communication system to a radar receiver by jointly optimizing the communication transmit beamformer and RIS phase shift matrix to maximize the radar probability of detection as in [10], while [11] employs two RISs, one at the communication transmitter and one at the receiver, to simultaneously enhance the communication signals and suppress mutual interference.

In this paper, we consider the clutter suppression problem for a bi-static radar system by deploying a hybrid RIS. Unlike a conventional reflect-only RIS, which can only adjust the phase shift of the metasurface elements, or an active RIS, which can also amplify the reflected signals using additional power consumption, here we propose to employ a hybrid RIS, which can adjust not only the phase but also the modulus of the RIS elements by potentially absorbing part of the received energy. Note that the hardware complexity required by the hybrid RIS does not dramatically exceed that of the conventional reflect-only RIS unless we want to leverage the absorbed signal energy for additional applications [12], [13], e.g., to conduct local channel estimation or localization at the RIS. On the other hand, since a hybrid RIS does not amplify the reflected signal, there is no additional noise introduced by active components, as would be the case with an amplifier. Thus, the hybrid RIS serves to provide a trade-off between its active and reflect-only counterparts in term of hardware complexity, power consumption, degrees of freedoms (DoFs) (e.g., adjustable modulus of the reflected signal), and the beamforming introduced by the RIS elements.

In this paper, we consider a radar system assisted by an RIS for target detection in a cluttered environment. The clutter scatterers are suppressed under two scenarios to improve the target detection performance: with and without target range cell knowledge. Specifically, when knowledge of the target range cell of interest is not available, the clutter mitigation problem is formulated by minimizing the received energy from the clutter echoes (including both the direct channel and the indirect channel relayed by the RIS). The resulting optimization problem can be formulated as a convex problem

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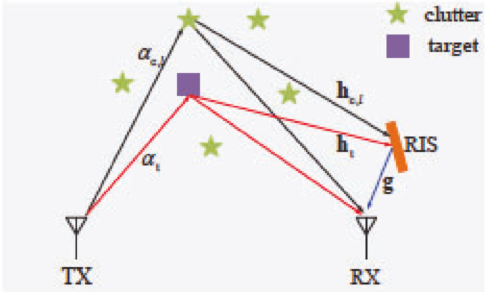

Fig. 1. A RIS-assisted bi-static radar system in cluttered environments.

and efficiently solved by standard numerical solvers. On the other hand, in applications where an area is scanned and the target location is postulated at different scanning points, the range cell of interest is known. In such cases, we propose to maximize the output signal-to-interference-plus-noise ratio (SINR), which results in a non-convex constrained optimization problem. We solve the problem using an alternating Dinkelbach algorithm together with semi-definite relaxation (SDR). Our numerical results show the proposed hybrid RIS designs can achieve considerable performance improvements over conventional reflect-only RIS for clutter suppression and target detection.

II. Signal Model and Problem formulation

We consider a single antenna bi-static radar system that probes an area containing L primary clutter scatterers, as shown in Fig. 1. The system is assisted by a hybrid RIS with K elements to suppress the clutter and improve target detection performance. Unlike a conventional reflect-only RIS, which can only adjust the phase ϑ_k of the k-th metasurface element, a hybrid RIS can also adjust its modulus by absorbing part of the energy of the impinging signal. In particular, the modulus ρ_k of the k-th element is adjustable with $\rho_k \in [0, 1]$ for the hybrid RIS, while that of the conventional reflect-only RIS is fixed with $\rho_k = 1$. The overall response at the k-th RIS element can be expressed as $\theta_k = \rho_k e^{\jmath\vartheta_k}$. Note that the absorbed signal energy can be utilized by a local processor for channel estimation or wireless localization to gain potential benefits over conventional reflect-only RIS at the cost of additional energy consumption and hardware complexity. In this work, we only investigate the benefit of the extra DoFs (reflectivity amplitude ρ_k) provided by the hybrid RIS for clutter suppression. Thus, the hardware design of the deployed RIS is not substanially more complicated than that of the reflect-only RIS.

In this paper, we consider the clutter suppression problem under two scenarios, i.e., with and without target range cell knowledge. When there is no knowledge of the target range cell, the RIS can be designed to mitigate the clutter. On the other hand, when a certain target range cell is considered, the RIS can be configured to maximize the illumination of the range cell for potential targets and suppress clutter interference at the same time.

A. Without Target Range Cell Knowledge

Let $\beta_{c,\ell}$ denote the radar cross section (RCS) of the ℓ-th clutter scatterer and define $\boldsymbol{\theta} = [\theta_1, \cdots, \theta_K]^T$. Assuming the transmitted radar waveform has unit power, the matched filter (MF) output of the noise-free received signal at the receiver (RX) when no target is present can be expressed as

$$y = \sum_{\ell}^{L} \beta_{c,\ell}(\alpha_{c,\ell} + \mathbf{h}_{c,\ell}^T \text{diag}(\boldsymbol{\theta})\mathbf{g}), \tag{1}$$

where $\alpha_{c,\ell}$ denotes the response of the channel from the transmitter (TX) to the ℓ-th clutter scatterer and then to the RX, $\mathbf{h}_{c,\ell}$ is the channel vector from the TX to the ℓ-th clutter scatterer and then to the RIS, and g denotes the channel vector from the RIS to the RX. The problem of interest is to mitigate the clutter by designing the RIS response, i.e., both its modulus coefficients and phase shifts, for better target detection performance when targets are present. Specifically, the clutter suppression problem can be formulated as minimizing the power of the received clutter echoes:

$$\min_{\boldsymbol{\theta}} \quad \sum_{\ell=1}^{L} \sigma_{c,\ell}^2 |\alpha_{c,\ell} + \mathbf{h}_{c,\ell}^T \text{diag}(\boldsymbol{\theta})\mathbf{g}|^2 \tag{2a}$$

$$\text{s.t. } |\boldsymbol{\theta}(k)| \leq 1, \forall k, \tag{2b}$$

where $\sigma_{c,\ell}^2$ is defined assuming a Gaussian distribution for the RCS scattering: $\beta_{c,\ell} \sim \mathcal{CN}(0, \sigma_{c,\ell}^2)$. We will show that the extra DoFs provided by the absorbing modulus coefficients of the RIS enable the clutter to be significantly mitigated with a sufficiently large number of RIS elements. This is not possible by only adjusting the phase of the RIS elements as in a conventional reflect-only RIS.

B. With Target Range Cell Knowledge

As a standard practice in radar signal detection [14], we consider testing for the presence of a target within a hypothesized range cell. Specifically, the target is assumed to be located within a given region that is divided into multiple range cells and the detection is performed on each cell in a sequential fashion. In this subsection, we propose to utilize information about each range cell under test to design the RIS, and in turn to further improve target detection performance. Let β_t denote the target RCS, α_t the channel coefficient from the TX to the target and then to the RX, and $\mathbf{h}_t$ the channel vector from the TX to the target and then to the RIS. The MF output of the noise-free received signal is given by

$$\begin{aligned} y = {} & \beta_t(\alpha_t + \mathbf{h}_t^T \text{diag}(\boldsymbol{\theta})\mathbf{g}) \\ & + \sum_{\ell}^{L} \beta_{c,\ell}(\alpha_{c,\ell} + \mathbf{h}_{c,\ell}^T \text{diag}(\boldsymbol{\theta})\mathbf{g}). \end{aligned} \tag{3}$$

The design aims to maximize the signal-to-interference-plus-noise ratio (SINR):

$$\max_{\boldsymbol{\theta}} \quad \frac{|\alpha_t + \mathbf{h}_t^T \text{diag}(\boldsymbol{\theta})\mathbf{g}|^2}{\sum_{\ell=1}^{L} \sigma_{c,\ell}^2 |\alpha_{c,\ell} + \mathbf{h}_{c,\ell}^T \text{diag}(\boldsymbol{\theta})\mathbf{g}|^2 + \sigma^2} \tag{4a}$$

$$\text{s.t. } |\boldsymbol{\theta}(k)| \leq 1, \forall k, \tag{4b}$$

where σ^2 is the noise variance. Note that the target RCS β_t is not required in the above formulation since it simply scales the cost function and will not affect the solution.

Note that the above formulations assume knowledge of the clutter RCS variance $\sigma_{c,\ell}^2$ and the channel coefficients $\alpha_{c,\ell}$, $\mathbf{h}_{c,\ell}$, α_t, $\mathbf{h}_t$, and $\mathbf{g}$. Although the target RCS β_t (which is not required in the design) is generally unknown prior to target detection, we assume knowledge of the channel information related to the locations of the TX, RX, and range cell, as well as the transmit power, which can be learned through training and calibration.

III. Proposed Solutions

In this section, we develop solutions to the optimization problems posed above with or without range cell knowledge, i.e., (2) and (4).

A. RIS Design without Range Cell Knowledge

While the clutter suppression problem in (2) is a nonlinear constrained optimization problem whose solution cannot be obtained directly, it can be reformulated as a convex problem and thus a global optimum solution can be efficiently obtained using standard optimization packages, e.g., CVX. Specifically, with $\mathbf{d} = [\sigma_{c,1}\alpha_{c,1}, \cdots, \sigma_{c,L}\alpha_{c,L}]^T$, problem (2) can be equivalently written as

$$\min_{\boldsymbol{\theta}} \quad \left\|\mathbf{d} + \mathbf{A}\boldsymbol{\theta}\right\|_2^2 \tag{5a}$$

$$\text{s.t. } |\boldsymbol{\theta}(k)| \leq 1, \ \forall k, \tag{5b}$$

where $\mathbf{A}$ is an $L \times K$ matrix whose ℓ-th row is defined as $\sigma_{c,\ell}\mathbf{h}_{c,\ell} \circ \mathbf{g}$, where $\circ$ denotes the element-wise product. It can be seen that problem (5) is convex and can be efficiently solved.

The problem formulation for the design using the hybrid RIS can be easily transformed to one involving a conventional reflect-only RIS by changing the constraint in (2) to $|\boldsymbol{\theta}(k)| = 1, \forall k$, i.e.,

$$\min_{\boldsymbol{\theta}} \quad \left\|\mathbf{d} + \mathbf{A}\boldsymbol{\theta}\right\|_2 \tag{6a}$$

$$\text{s.t. } |\boldsymbol{\theta}(k)| = 1, \ \forall k, \tag{6b}$$

which is a non-convex problem due to the constant-modulus constraint. This problem can be recast as a unit-modulus constrained quadratic program and solved by applying semidefinite relaxation (SDR) [15]. Recently, a fast solution to least-squares problems with unit-modulus constraints was proposed in [16] based on gradient projection. For completeness, we summarize the procedure for solving problem (6) in Algorithm 1 below. Note that in the algorithm description, $\lambda_{\max}(\mathbf{X})$ denotes the largest eigenvalue of $\mathbf{X}$ and $\dagger$ denotes the pseudo-inverse operator.

Algorithm 1 Gradient Projection Method to Solve (6)

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input: Channel matrices $\mathbf{H}$, $\mathbf{G}$, and $\mathbf{D}$.

initialization: Let the iteration index $i = 0$, $\boldsymbol{\theta}^{(0)} = e^{\jmath\angle(-\mathbf{A}^\dagger\mathbf{d})}$, and $\beta = \frac{0.999}{\lambda_{\max}(\mathbf{A}^H\mathbf{A})}$.

repeat

1) Gradient: $\boldsymbol{\xi}^{(i+1)} = \boldsymbol{\theta}^{(i)} - \beta\mathbf{A}^H(\mathbf{d} + \mathbf{A}\boldsymbol{\theta}^{(i)})$.
2) Projection: $\boldsymbol{\theta}^{(i+1)} = e^{\jmath\angle(\boldsymbol{\xi}^{(i+1)})}$.
3) Set $i = i + 1$

until convergence.

B. RIS Design with Range Cell Knowledge

Problem (4) is nonconvex and cannot be solved in closed-form. In the following, an iterative method is developed to solve it. Specifically, the numerator of the cost function of (4) is equivalently expressed as

$$|\alpha_t + \mathbf{h}_t^T\text{diag}(\boldsymbol{\theta})\mathbf{g}|^2 = |\alpha_t + \mathbf{f}_t^H\boldsymbol{\theta}|^2 = \bar{\boldsymbol{\theta}}^H\mathbf{F}_t\bar{\boldsymbol{\theta}}, \tag{7}$$

where $\mathbf{f}_t^* = \mathbf{h}_t \circ \mathbf{g}$, $\bar{\boldsymbol{\theta}} = [\boldsymbol{\theta}^T \ 1]^T$ and

$$\mathbf{F}_t = \begin{bmatrix} \mathbf{f}_t\mathbf{f}_t^H & \mathbf{f}_t\alpha_t \\ \mathbf{f}_t^H\alpha_t^* & |\alpha_t|^2 \end{bmatrix}. \tag{8}$$

Similarly, the clutter-related part of the denominator of the cost function in (4) can be written as

$$\sigma_{c,\ell}^2|\alpha_{c,\ell} + \mathbf{h}_{c,\ell}^T\text{diag}(\boldsymbol{\theta})\mathbf{g}|^2 = \bar{\boldsymbol{\theta}}^H\mathbf{F}_{c,\ell}\bar{\boldsymbol{\theta}}\sigma_{c,\ell}^2, \tag{9}$$

where

$$\mathbf{F}_{c,\ell} = \begin{bmatrix} \mathbf{f}_{c,\ell}\mathbf{f}_{c,\ell}^H & \mathbf{f}_{c,\ell}\alpha_{c,\ell} \\ \mathbf{f}_{c,\ell}^H\alpha_{c,\ell}^* & |\alpha_{c,\ell}|^2 \end{bmatrix}, \tag{10}$$

with $\mathbf{f}_{c,\ell}^* = \mathbf{h}_{c,\ell} \circ \mathbf{g}$.

Thus, the optimization problem in (4) can be rewritten as

$$\max_{\boldsymbol{\theta}} \ \frac{\bar{\boldsymbol{\theta}}^H\mathbf{F}_t\bar{\boldsymbol{\theta}}}{\sum_{\ell=1}^{L}\bar{\boldsymbol{\theta}}^H\mathbf{F}_{c,\ell}\bar{\boldsymbol{\theta}}\sigma_{c,\ell}^2 + \sigma^2} \tag{11a}$$

$$\text{s.t. } |\bar{\boldsymbol{\theta}}(k)| \leq 1, \ k = 1, \cdots, K, \tag{11b}$$

$$\bar{\boldsymbol{\theta}}(K+1) = 1. \tag{11c}$$

This is a fractional quadratically constrained quadratic programming (QCQP) problem and can be solved using SDR along with the Dinkelbach algorithm. In the following, we first use SDR to convert (11) to a fractional programming problem by dropping the rank-one constraint. Let $\boldsymbol{\Theta} = \bar{\boldsymbol{\theta}}\bar{\boldsymbol{\theta}}^H$ to obtain the SDR version of (11) as

$$\max_{\bar{\boldsymbol{\Theta}}} \ \frac{\text{tr}(\boldsymbol{\Theta}\mathbf{F}_t)}{\sum_{\ell=1}^{L}\text{tr}(\bar{\boldsymbol{\Theta}}\mathbf{F}_{c,\ell})\sigma_{c,\ell}^2 + \sigma^2} \tag{12a}$$

$$\text{s.t. } \boldsymbol{\Theta}(k,k) \leq 1, k = 1, \cdots, K, \tag{12b}$$

$$\boldsymbol{\Theta}(K+1, K+1) = 1, \tag{12c}$$

which is a fractional programming problem and can be solved by the Dinkelbach algorithm in polynomial time [17]. Specifically, by introducing a slack variable λ, problem (12) becomes

$$\max_{\boldsymbol{\Theta},\lambda} \ \text{tr}(\boldsymbol{\Theta}\mathbf{F}_t) - \lambda\Big(\sum_{\ell=1}^{L}\text{tr}(\boldsymbol{\Theta}\mathbf{F}_{c,\ell})\sigma_{c,\ell}^2 + \sigma^2\Big) \tag{13a}$$

$$\text{s.t. (12b), (12c).} \tag{13b}$$

The above problem can be solved by alternatingly optimizing the cost function with respect to (w.r.t.) $\mathbf{\Theta}$ and λ. In particular, by fixing λ to the value obtained in the i-th iteration, $\lambda^{(i)}$, we can obtain $\mathbf{\Theta}^{(i+1)}$ by solving

$$\max_{\bar{\mathbf{\Theta}}} \operatorname{tr}(\mathbf{\Theta}\mathbf{F}_{\mathrm{t}}) - \lambda^{(i)}\Big(\sum_{\ell=1}^{L}\operatorname{tr}(\mathbf{\Theta}\mathbf{F}_{\mathrm{c},\ell})\sigma_{\mathrm{c},\ell}^2 + \sigma^2\Big) \tag{14a}$$

$$\text{s.t. (12b), (12c),} \tag{14b}$$

which is a convex problem. Next, we find λ by fixing $\mathbf{\Theta}$ to the value obtained from the latest update, $\bar{\mathbf{\Theta}}^{(i+1)}$, in which case $\lambda^{(i+1)}$ is solved in closed-form as

$$\lambda^{(i+1)} = \frac{\operatorname{tr}(\bar{\mathbf{\Theta}}\mathbf{F}_{\mathrm{t}})}{\sum_{\ell=1}^{L}\operatorname{tr}(\bar{\mathbf{\Theta}}\mathbf{F}_{\mathrm{c},\ell})\sigma_{\mathrm{c},\ell}^2 + \sigma^2}. \tag{15}$$

The alternating process is repeated until the algorithm converges, i.e., the improvement of the cost function over two adjacent iterations is smaller than a predefined tolerance ϵ. After convergence, the optimum solution is denoted as $\hat{\mathbf{\Theta}}$.

After solving (12) through the iterative Dinkelbach algorithm, we need to convert the optimum solution $\hat{\mathbf{\Theta}}$ to (12) into a feasible solution $\hat{\boldsymbol{\theta}}$ to (11). This can be achieved through a randomization approach [15]. Specifically, given the optimum $\hat{\mathbf{\Theta}}$, a set of Gaussian random vectors are generated, i.e., $\boldsymbol{\xi}_j \sim \mathcal{CN}(\mathbf{0}, \hat{\mathbf{\Theta}})$, $j = 1, \cdots, J$, where J is the number of randomization trials. Since the $\boldsymbol{\xi}_j$ are not always feasible for the modulus constraints in (11), we need to first normalize them through $\bar{\boldsymbol{\xi}}_j = \boldsymbol{\xi}_j / \boldsymbol{\xi}_j(K+1)$ to satisfy the constraint $|\bar{\theta}(K+1)| = 1$. Then, to meet the constraint $|\bar{\theta}(k)| \leq 1$, the feasible solution can be further recovered by setting $\hat{\boldsymbol{\xi}}_j(k) = e^{\jmath\angle(\bar{\boldsymbol{\xi}}_j(k))}$ if $|\bar{\boldsymbol{\xi}}_j(k)| > 1$. Finally, a rank-one solution can be obtained as

$$\hat{\boldsymbol{\theta}} = \arg\max_{\{\hat{\boldsymbol{\xi}}_j\}} \frac{\hat{\boldsymbol{\xi}}_j^H \mathbf{F}_{\mathrm{t}} \hat{\boldsymbol{\xi}}_j}{\sum_{\ell=1}^{L} \hat{\boldsymbol{\xi}}_j^H \mathbf{F}_{\mathrm{c},\ell} \hat{\boldsymbol{\xi}}_j \sigma_{\mathrm{c},\ell}^2 + \sigma^2}. \tag{16}$$

Similar to the solution for the design without range cell knowledge in Section III-A, the formulation for the design using reflect-only RIS can be easily obtained by changing the constraint (11b) to $|\bar{\theta}(k)| = 1$ for $k = 1, \cdots, K+1$. The solution can be accordingly adjusted with the new constraint without imposing additional difficulties.

IV. Numerical Simulations

In this section, simulation results are presented to evaluate the capability of the hybrid RIS for clutter suppression. The performance of the hybrid RIS is compared with that of the conventional reflect-only RIS. Specifically, the proposed hybrid RIS design without knowledge of the target range cell information is denoted as **hybrid RIS**, while that of the reflect-only RIS design is denoted as **passive RIS**. With range cell information, the corresponding designs are referred to as knowledge-aided hybrid RIS (**KA hybrid RIS**) and knowledge-aided passive RIS (**KA passive RIS**), respectively. The signal-to-noise ratio (SNR) and clutter-to-noise ratio (CNR) are defined as

$$\text{SNR} = \frac{\sigma_{\mathrm{t}}^2}{\sigma^2} \qquad \text{CNR} = \sum_{\ell=1}^{L}\frac{\sigma_{\mathrm{c},\ell}^2}{\sigma^2}, \tag{17}$$

where σ_{t}^2 denotes the variance of the target RCS β_{t}. In the simulations, we assume $L = 6$ and noise variance $\sigma^2 = 10^{-4}$. All results are averaged over 100 random channel realizations.

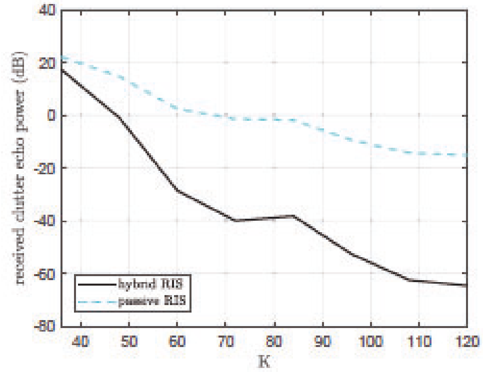

Fig. 2. Performance of the design without target range cell knowledge when $\sigma_{\mathrm{c},\ell}^2 = 30$ dB.

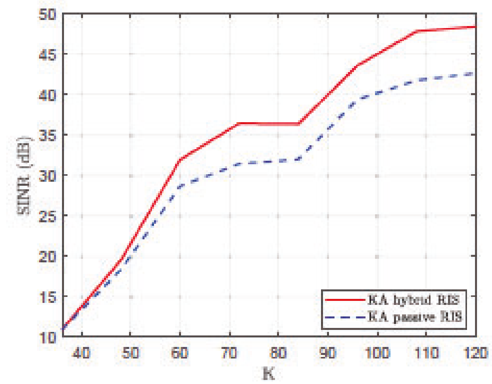

Fig. 3. Performance of the design with target range cell knowledge when CNR = 40 dB and SNR = 40 dB.

Fig. 2 and Fig. 3 evaluate the performance of the proposed schemes in terms of the cost function of the optimization problem, i.e., the received clutter echo power and output SINR. Specifically, Fig. 2 shows the received clutter echo power versus the number of RIS elements K when $\sigma_{\mathrm{c},\ell}^2 = 30$ dB $\forall\ell$. It can be seen that the performance of both the hybrid and reflect-only RIS improves when the number of RIS elements increases. This is because a larger K means more DoFs for the RIS to suppress the clutter. In addition, the hybrid RIS outperforms the reflect-only RIS for all K, especially for larger K due to the availability of extra DoFs from the adaptivity of the modulus of the RIS elements. A similar performance trend can be observed in Fig. 3, where the output SINR is plotted against K when the target range cell knowledge is available.

The above results demonstrate that the proposed schemes offer better clutter suppression performance or higher output SINR, which is expected to yield better performance in detec-

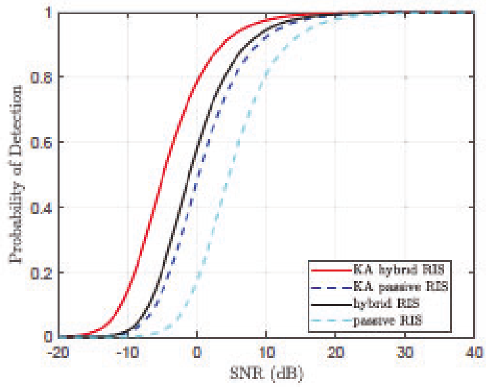

Fig. 4. Probability of detection versus SNR for a given probability of false alarm $P_f = 10^{-4}$, CNR = 40 dB, and $K = 96$.

tion than conventional reflect-only RIS assisted systems. To see this, we consider the following hypothesis test:

$$
\begin{aligned}
\mathcal{H}_0 : y &= \sum_{\ell}^{L} \beta_{\mathrm{c},\ell}\Big(\alpha_{\mathrm{c},\ell} + \mathbf{h}_{\mathrm{c},\ell}^{T}\mathrm{diag}(\boldsymbol{\theta})\mathbf{g}\Big) + w, \\
\mathcal{H}_1 : y &= \beta_{\mathrm{t}}\Big(\alpha_{\mathrm{t}} + \mathbf{h}_{\mathrm{t}}^{T}\mathrm{diag}(\boldsymbol{\theta})\mathbf{g}\Big) \\
&\quad + \sum_{\ell}^{L} \beta_{\mathrm{c},\ell}\Big(\alpha_{\mathrm{c},\ell} + \mathbf{h}_{\mathrm{c},\ell}^{T}\mathrm{diag}(\boldsymbol{\theta})\mathbf{g}\Big) + w, \qquad (18)
\end{aligned}
$$

where under the H_0 hypothesis, the radar observes only clutter and noise $w \sim \mathcal{CN}(0, \sigma^2)$, while under the H_1 hypothesis, the radar observation y contains target echoes. The received signal is then processed using the energy detector [18]:

$$
|y|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \zeta, \qquad (19)
$$

where ζ is a threshold set based on a desired probability of false alarm P_f.

Fig. 4 shows the probability of detection versus the SNR for a probability of false alarm of $P_f = 10^{-4}$, CNR = 40 dB, and $K = 64$. It is seen that the hybrid RIS substantially outperforms the reflect-only RIS in both cases. In addition, the knowledge-aided designs are better than those without knowledge of the target cell since the additional information is employed to further improve the output SINR which in turn improves target the detection performance.

V. Conclusions

We proposed an approach to improve radar target detection performance in cluttered environments by leveraging hybrid RIS. When the target range cell information is not available, the hybrid RIS, which can adjust both the phase and modulus of its elements, is designed to suppress reflections from the clutter scatterers by minimizing the received clutter echo energy. The resulting optimization problem is convex. On the other hand, when knowledge of the areas to be monitored is available, the hybrid RIS is designed to improve target detection performance by maximizing the received SINR. The resulting nonconvex problem was solved through a SDR-assisted fractional programming algorithm. Numerical results show that the proposed hybrid RIS-assisted radar system offers significant performance gains over the conventional reflect-only RIS-assisted system with or without target range cell knowledge.

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