Abstract—In this paper, we study a communication-centric integrated sensing and communication (ISAC) approach, where an access point (AP) communicates with users, while a passive radar (PR) is present in the environment. We investigate the deployment of a reconfigurable intelligent surface (RIS) to enable the PR to localize a target. We derive an optimization problem for updating the phase shifters of the RIS per epoch. Due to the limited information at the PR, such as unknown payload information and unknown number of targets in the scene, we propose two methods capable of performing joint angle of arrival estimation and detection of the targets. We demonstrate the superior performance of the methods onto the proposed setting through numerical simulations, in comparison to a no-RIS baseline scheme.

Index Terms—Reconfigurable Intelligent Surfaces, Integrated Sensing and Communications, RIS, ISAC, 6G

I. INTRODUCTION

Research has begun to piece together a speculative vision of 6G by studying potential future services and applications, identifying market demands, and finding disruptive technologies [1]. A vast range of services must be supported by 6G, including blockchain, haptic telemedicine, VR/AR remote services, holographic teleportation, and huge eXtended reality (XR) capabilities. There is no doubt that 6G has advantages beyond connectivity. It will combine new functions like sensing and computing, opening up new services and employing better environmental data for artificial intelligence and machine learning. However, as [2] emphasizes, such bandwidth-hungry applications need for a $10^3$× increase in capacity. Furthermore, it is anticipated that by 2030, mobile data use per mobile broadband subscriber would increase by a factor of 50, from 5.3GB in 2020 to 257GB in 2030. Nevertheless, there are several enabling technologies (such as sub-6 GHz and mmWave frequencies) and reconfigurable intelligent surface (RIS).

By ingeniously reconfiguring the wireless propagation environment, reconfigurable intelligent surfaces (RISs) have drawn a lot of attention for their potential to increase the capacity and coverage of wireless sensor networks. A RIS [3] is composed of an array of reflecting elements capable of reconfiguring incident signals, thanks to its two-dimensional material structure with programmable macroscopic physical characteristics. Since the RIS can reconfigure the electromagnetic (EM) incident wave, the wireless channel between different nodes of the wireless network could be altered. In fact, RIS’s relatively low energy consumption is one of its most appealing features because it allows for the amplification and transmission of incoming signals without the use of a power amplifier. However, because of the inexpensive cost of RIS, it may be unusually large and sprawl the entire wall of a building [4]. Instead, phase shifts applied by each reflecting element are properly designed in order to combine each reflected signal in a useful manner. In the literature, they are also referred to as large intelligent surface/antennas (LISA) [5], [6] or intelligent reflecting surfaces (IRSs) [7], [8]. Recently, RISs have been used to aid many profound applications in wireless communications, such as beamforming [9], [10], security [11], [12], orthogonal frequency-division multiplexing (OFDM) [13], [14], millimeter-wave channel estimation [15]–[18] just to name a few. There is a handful of significant advantages that could be leveraged from RIS deployment [19] in various wireless communication scenarios, such as their capability of improving the spectral and energy efficiency [20], [21], their ease of deployment and environment friendliness, compatibility with already existing standards [22], and secure wireless communications [23]. For more advantages in terms of security, energy efficiency and coverage, the interested reader is referred to [24].

Within the last 80 years, passive radar, which indicates the localization of a target by radar data without the use of own controlled emissions, had been thoroughly investigated [25]–[28]. It is highlighted in [29], that RIS is foreseen to be a key enabler for advanced localization and sensing by passive radar (PR). The deployment of passive radars possess exceptional advantages, due to their low cost [30] in terms of procurement, operation and maintenance, as well as its ability in covert operation. In PR, it is crucial to locate targets with minimal information. Indeed, the passive radar, unlike traditional radar, is protocol-agnostic. That is, the PR has no knowledge about transmit waveform information. On the other hand, PR sometimes fail to perform target localization due to lack of aid from active components.

A challenging, yet interesting, feature of 6G is integrated sensing and communications (ISAC), where the designed waveforms convey communication, as well as sensing information [1]. This allows for shared spectrum, power efficiency, in addition to hardware efficiency. ISAC can be split into three broad categories, where the first aims at a joint design, offering trade-offs between sensing and communications. For example, the work in [31] derives beamforming matrices for ISAC systems, under practical assumptions, such as imperfect channel state information, while [32] considers a joint design for variable length time snapshots. Another category
is radar-centric ISAC, where the main goal is to embed communication information onto a radar waveform, such as a chirp [33]. The last category is communication-centric ISAC, where one simply performs sensing using a known communication waveform, such as OFDM. The priority in this case is communications, and hence, we may consider the contributions that bounce towards the PR. Meanwhile, the authors in [34] propose an adaptive RIS phase shifter based on normalized least mean squares (NLMS) filtering. Therefore, the proposed methods do not comprise of reflections resulting from targets being localized in the scene. In particular, the received signal in [37] is the direct path and the reflection resulting from the RIS. In contrast to our proposed model, where the PR performs spatial beamforming towards the RIS and focuses on the reflections bouncing off the targets towards the RIS, which in turn mirrors these bounces towards the PR. Meanwhile, the authors in [38] aim at optimizing the RIS phase shift coefficients to maximize the differences of received signal strength (RSS) values as the location changes. A similar approach utilizing RSS information appears in [39]. As opposed to [38], [39], we consider the contributions that bounce towards the RIS, then reflected towards the PR. In addition, our work does not utilize the RSS to perform target localization, as it relies on the angle of arrival (AoA) information of the different reflections.

To that purpose, we have summarized our contributions below.

- **A new architecture towards target localization.** This work describes a new RIS-aided setting dedicated for target localization, which is well-suited for communication-centric ISAC systems. More specifically, a PR and an RIS are considered, where the RIS "mirrors" the reflections resulting from targets in the scene towards the PR.

- **RIS matrix optimization.** Upon "mirroring" back the reflections towards the PR, the RIS configures suitable phase shifters that could properly reflect the reflections caused only by the targets to localize.

- **Localization without knowledge of number of targets.** The PR being unaware of the dynamics of the environment, we believe that joint estimation and detection of the targets is an important task that should be carried out at the PR, with minor information about the signaling being used. Motivated by this task, we propose two methods for target localization without the need to resort to techniques that require source number enumeration, such as Akaike’s information criterion (AIC) [40] and minimum description length (MDL) [41]. The proposed methods are based on normalized least mean squares (NLMS) filtering. Therefore, the proposed methods perform joint estimation and detection of targets.

Furthermore, we unveil some important insights, i.e.

- A 20 dB gain in terms of required signal-to-noise ratio (SNR) to attain an mean squared error (MSE) of 0.2 is achieved when utilizing the RIS aided target localization approach, with 16 reflective elements.

- Since the proposed methods perform simultaneous detection of number of targets, we also study the probability of detection. In this respect, a 16 dB gain in terms of required SNR for a probability of detection equal to 0.9 is attained with 16 reflective elements, as compared to a no-RIS approach. A supplemental 4 dB gain is achieved, when doubling the number of reflective elements.

- With respect to successful recovery probability (SRP), we observe gains in the order of 18 dB when localizing via the proposed RIS-aided architecture.

**C. Organization and Notations**

The detailed structure of this paper is given as follows,

- Section [II] presents the system model which includes the AP, targets and an RIS in the scene. The section describes how the PR senses the reflections mirrored by the RIS and mathematically formulates the problem at hand.

- Section [III] demonstrates the reflection matrix optimization technique. More specifically, it formulates and solves phase shifter components per epoch, relative to the RIS.

- Section [IV] presents the beamforming step at PR level. In particular, the PR should look towards the RIS in order to properly acquire all the reflections caused by the K targets. This section is dedicated towards adjusting the PR’s beamforming weights.

- Section [V] presents the two methods for target localization performed at the PR. The methods are batch and
The signal would then hit the PR, enabled by the reconfigurable behavior of the RIS. Furthermore, the complex coefficient \(a_M(\theta)\) is the steering matrix, which results from the contribution of each path between the targets and the RIS, namely
\[
A(\Theta_{RIS}^{1:K}) = [a_M(\theta_1^{RIS}) \ a_M(\theta_2^{RIS}) \ldots a_M(\theta_K^{RIS})],
\]
where \(a_M(\theta)\in\mathbb{C}^{M \times 1}\) is the steering vector at the output of the \(M\)-elements of the RIS. The concatenation of all steering vectors defines the array manifold, \(A(\Theta_{RIS}^{1:K})\in\mathbb{C}^{M \times K}\). It is worth noting that this paper does not assume any structure on \(a_M(\theta)\). The signal \(s(t)\) contains scaled and delayed versions of the original transmitted signal \(s(t)\), and is represented as
\[
s(t) = \begin{bmatrix} \alpha_1s(t - \tau_{AP} - \tau_{RIS}^{1}) \\ \alpha_2s(t - \tau_{AP} - \tau_{RIS}^{2}) \\ \vdots \\ \alpha_Ks(t - \tau_{AP} - \tau_{RIS}^{K}) \end{bmatrix} \in\mathbb{C}^{K \times 1},
\]
where \(\tau_{AP}\) is the propagation delay between the AP and the \(k^{th}\) target, \(\tau_{RIS}^{k}\) is the propagation delay between the \(k^{th}\) target and the RIS, and \(\tau_{RIS}^{k}\) is the propagation delay between the AP and the RIS. Furthermore, the complex coefficient \(\alpha_k\), for \(k = 1\ldots K\), is the reflection gain, taking into account large scale fading effects, resulting from the path between the AP towards the \(k^{th}\) target then towards the RIS. Likewise, \(\alpha_0\) is the complex coefficient taking into account the channel gain between the AP and the RIS. Furthermore, the reflected signal from the RIS towards the PR is expressed as
\[
x_n(t) = v_n^T\left(A(\Theta_{RIS}^{1:K})s(t) + \alpha_M(a_M(\theta)RIS)s(t - \tau_{RIS}^{1})\right),
\]
where \(v_n\in\mathbb{C}^{M \times 1}\) is the phase shifts due to the reflecting elements of the RIS at the \(n^{th}\) epoch. We define the epoch as a period of time receiving a realization of \(r(t)\) defined in equation [1]. The final received signal at the PR is expressed over three counterparts as follows
\[
y_n(t) = \rho_{RIS}^{PR}a(\theta_{RIS}^{PR})x_n(t - \tau_{RIS}^{PR}) + \rho_{AP}^{PR}a(\theta_{AP}^{PR})s(t - \tau_{AP}^{PR}) + \sum_{k=1}^{K} \rho_k a(\theta_k^{PR})s(t - \tau_{AP}^{PR} - \tau_{RIS}^{k}) + \epsilon_n(t),
\]
where \(y_n(t)\in\mathbb{C}^{N \times 1}\) is the received signal at the PR. The first term, i.e. \(\rho_{RIS}^{PR}a(\theta_{RIS}^{PR})x_n(t - \tau_{RIS}^{PR})\), contains all information gathered at the RIS and reflected back towards the PR. The second term, namely \(\rho_{AP}^{PR}a(\theta_{AP}^{PR})s(t - \tau_{AP}^{PR})\), consists of the direct LoS between the AP and the PR. The third term, that is \(\sum_{k=1}^{K} \rho_k a(\theta_k^{PR})s(t - \tau_{AP}^{PR} - \tau_{RIS}^{k})\), contains \(K\) target contributions that propagated from the AP towards the targets then bounced off the targets towards the PR. The propagation delay \(\tau_{RIS}^{k}\) is the delay between the RIS and the PR, \(\tau_{AP}^{PR}\) is the delay between AP and PR, and \(\tau_{RIS}^{k}\) is the delay between the \(k^{th}\) target and
the PR. Moreover, the large scale fading gains $\rho_k$’s are defined in a similar manner as $\alpha_k$’s. Furthermore, the noise term $\epsilon_i(t)$ is additive white Gaussian background noise. Sampling at $L$ time instances, we have

$$Y_n = [y_n(1) \ y_n(2) \ldots \ y_n(L)]$$

$$= \rho_{kRIS}a(\theta_{kRIS})x_n + \rho_{kAP}a(\theta_{AP})s_{kAP} + \sum_{k=1}^{K} \rho_k a(\theta_k) s_k + E_n,$$

where $Y_n \in \mathbb{C}^{Nm \times L}$ is the sampled data matrix at the PR at the $n^{th}$ epoch. Also,

$$x_n = [x_n(t_1) \ x_n(t_2) \ldots \ x_n(t_L)],$$

$$s_{kAP}^{PR} = \begin{bmatrix} s(t_1 - \tau_{AP})^T \\
+ \ldots \\
+ s(t_L - \tau_{AP})^T \end{bmatrix},$$

$$s_{kPR}^{PR} = \begin{bmatrix} s(t_1 - \tau_{PR})^T \\
+ \ldots \\
+ s(t_L - \tau_{PR})^T \end{bmatrix},$$

$$E_n = [\epsilon_n(t_1) \ \epsilon_n(t_2) \ldots \ \epsilon_n(t_L)]^T.$$ (10)

Collecting all samples at different epochs in one data matrix, we now have the following at the PR,

$$Y = \begin{bmatrix} Y_1 \\
Y_2 \\
\vdots \\
Y_N \end{bmatrix} \in \mathbb{C}^{NM \times Nepoch \times L}. $$ (11)

Now, we are ready to address our problem, i.e. given our data matrix $Y$, which contains information over different trajectories, time instances and passive radar sensors, our objective is to estimate the angles of arrivals of the targets that bounced off the RIS towards the PR.

### III. Reflection Matrix Optimization

The RIS reflection matrix is used for radar-centric sensing performance enhancements. Our goal is to maximize the contributions of the $K$ targets collected at the RIS and minimize the power of all other contributions, which in this case come from the AP. At the $n^{th}$ epoch, one possible optimization problem would be to

$$\mathcal{P}_{RIS} : \begin{cases} 
\min_{\mathbf{v}} \| \mathbf{v}^H a(\theta_{RIS}) \|^2 \\
\text{s.t.} \ |\mathbf{v}| = 1.
\end{cases}$$ (12)

Note that in the above, we have decided not to create specific beams towards the PR, as we can have multiple PRs in the scene. Therefore, the objective aims at minimizing the known static contribution between AP and RIS. Also, the above problem acts on an instantaneous basis, that is it optimizes the reflection coefficients of the RIS based on observations at the $n^{th}$ epoch only. To minimize over all epochs, we propose the following criterion,

$$\mathcal{P}_{RIS} : \begin{cases} 
\min_{\mathbf{v}} \| \mathbf{v} a(\theta_{RIS}) \|^2 \\
\text{s.t.} \ |\mathbf{v}| = 1.
\end{cases}$$ (13)

where $\mathbf{v} = [\mathbf{v}_1 \ \mathbf{v}_2 \ldots \ \mathbf{v}_{Nepoch}]^T \in \mathbb{C}^{Nepoch \times M}$. The above problem is obviously a non-convex optimization problem. To this end, we propose to first relax the problem as follows: 1) solve the unconstrained optimization problem then 2) adapt the solution towards a feasible one. Following this approach, the solution of the unconstrained variant of $\mathcal{P}_{RIS}$ is

$$\mathbf{V} = \mathcal{P}_{a(\theta_{RIS})}^{\perp} : \mathbf{I}_M - \frac{1}{\| \mathbf{a}(\theta_{RIS}) \|^2} \mathbf{a}(\theta_{RIS}) \mathbf{a}^H(\theta_{RIS}^H),$$ (14)

which constitutes a one-time computation. Next, the solution is in-feasible, since there is no guarantee that $\mathbf{V}_{i,j}$ satisfies the constant modulus constraint.

$$\mathbf{V} = \exp \left\{ j \theta(\mathcal{P}_{a(\theta_{RIS})}^{\perp} \mathbf{I}) \right\},$$ (15)

where $\mathbf{I} \in \mathbb{C}^{M \times Nepoch}$ is a random matrix drawn from a standard Gaussian distribution. Note that the solution, $\mathbf{V}$ is independent of the signal $s(t)$, hence no signal knowledge is required at the RIS, as well as the PR.

### IV. Beamforming Towards RIS

First, let us assume that the PR beamforms towards the RIS using the same beamforming vector $\mathbf{w}$ over all time epochs as follows

$$\mathbf{Z} = \begin{bmatrix} \mathbf{w}^H \mathbf{Y}_1 \\
\mathbf{w}^H \mathbf{Y}_2 \\
\vdots \\
\mathbf{w}^H \mathbf{Y}_N \end{bmatrix} = [\mathbf{z}_1 \ldots \ \mathbf{z}_L] \in \mathbb{C}^{Nepoch \times L}. $$ (16)

Notice that the output of the beamformer at any epoch $n$ is given as follows

$$\mathbf{w}^H \mathbf{Y}_n = \rho_{RIS} \mathbf{w}^H a(\theta_{RIS}) x_n + \mathbf{w}^H \left( \rho_{AP} a(\theta_{AP}) s_{AP} + \sum_{k=1}^{K} \rho_k a(\theta_k) s_k + E_n \right).$$ (17)

Aiming at maximizing the output power over all epochs, we can propose the following optimization problem

$$\mathcal{P}_{1} : \begin{cases} 
\max_{\mathbf{w}} \sum_{n=1}^{N} \mathbf{R}_{x,x,n} \n\text{s.t.} \ \mathbf{w}^H a(\theta_{RIS}) = 1,
\end{cases}$$ (18)

where $\mathbf{R}_{x,x,n}$ is the output power contribution of the useful part looking in the direction of $\theta_{RIS}$

$$\mathbf{R}_{x,x,n} = |\alpha_n|^2 \mathbf{w}^H a(\theta_{RIS}) a^H(\theta_{RIS}) \mathbf{w},$$ (19)

where $\alpha_n = \rho_{RIS} \sqrt{x_n^H x_n^*}$. The Lagrangian function associated with the above optimization problem is given as follows

$$\mathcal{L}(\mathbf{w}, \lambda) = |\alpha|^2 \mathbf{w}^H a(\theta_{RIS}) a^H(\theta_{RIS}) \mathbf{w} - \lambda (\mathbf{w}^H a(\theta_{RIS}) - 1),$$ (20)
where \(|\alpha|^2 = \sum_{n=1}^{N} |\alpha_n|^2\). Deriving with respect to \(w\), we get the following expression
\[
\frac{\partial}{\partial w} \mathcal{L}(w, \lambda) = 2|\alpha|^2\alpha^H(\theta_{RIS}^R)\alpha H(\theta_{RIS}^R)w - \lambda\alpha(\theta_{RIS}^R),
\]
which is null at
\[
w = \frac{\alpha(\theta_{RIS}^R)}{||\alpha(\theta_{RIS}^R)||^2},
\]
and
\[\lambda = 2|\alpha|^2.\]

To this end, and after beamforming via equation (22), our model becomes
\[
Z_n = w^H Y_n = \rho^R_{RIS} x_n + i_n + \epsilon_n,
\]
with
\[i_n = \rho^P_{AP} \beta(\theta_{AP}^P) s^P_{AP} + \sum_{k=1}^{K} \rho_k \beta(\theta_{k}^P) s^P_k,
\]
where \(\epsilon_n = w^H E_n\) and \(\beta(\theta) = w^H a(\theta)\) is the output of the beampattern used with our beamforming vector to maximize the power in the direction of \(\theta_{RIS}^R\). With increasing number of antennas for ULAs, it is easily verified that \(\beta(\theta) \xrightarrow{N_{PR} \to \infty} 0\) for all \(\theta \neq \theta_{RIS}^R\). Therefore, this means that all signal contributions that are not reflected by the RIS, \(i_n \xrightarrow{N_{PR} \to \infty} 0\).

After beamforming at each time epoch, the collected data are stacked as
\[
Z = \begin{bmatrix}
w^H Y_1 \\
w^H Y_2 \\
\vdots \\
w^H Y_{N_{epoch}}
\end{bmatrix} = \begin{bmatrix}
z_1 \\
z_2 \\
\vdots \\
z_L
\end{bmatrix},
\]
where \(Z \in \mathbb{C}^{N_{epoch} \times L}\) is the beamformed data matrix at the PR over all epochs and time samples. In the next section, we describe two methods that process \(Z\) in two different manners, i.e. as a batch or sequentially.

V. TARGET LOCALIZATION

Given a matrix \(Z\) at the passive radar, the task is to estimate all angles within \(\Theta_{1:K}^{RIS}\), which consists of all target AoA information. However, in many situations, such as dynamic environments, the number of targets, i.e. \(K\), may be unknown. To this end, consider the output of the sum-and-delay beamformer at direction \(\theta\) utilizing the steering vector \(\mathbf{v}(\theta)\) at the \(\ell^{th}\) snapshot, namely
\[
p(\ell) = \mathbf{a}(H) H z_\ell.
\]
Then, we can define the error cost function that we try to minimize at each snapshot, i.e.
\[
C(\ell) = \mathbb{E}(|e(\ell)|^2),
\]
where \(e(\ell) = p(\ell) - \mathbf{a}(H) H z_\ell\). The least-mean square aims at minimizing the above cost. First, we take the gradient with respect to \(\mathbf{a}\) to get
\[
\nabla_a C(\ell) = 2\mathbb{E}\{\nabla_a |e(\ell)| e^*(\ell)\} = -2\mathbb{E}\{p(\ell) - \mathbf{a}(H) H z_\ell\} z_\ell^*,
\]
where the last step is due to the gradient’s value, \(\nabla_a |c(\ell)| = -z_\ell\). Thanks to \(\nabla_a C(\ell)\), the least mean squares (LMS) filter can now focus towards the steepest ascent of \(C(\ell)\) by taking a direction opposite to \(\nabla_a C(\ell)\), namely
\[

\hat{\mathbf{a}}_{\ell+1}(\theta) = \hat{\mathbf{a}}_\ell(\theta) - \frac{H}{2} \left[\nabla_a C(\ell)\right]_{\mathbf{a} = \hat{\mathbf{a}}_\ell}
\]
\[= \hat{\mathbf{a}}_\ell(\theta) + \mu \mathbb{E}\{p(\theta) - \hat{\mathbf{a}}_\ell(H) z_\ell\}^* z_\ell^*,\]
where \(\frac{H}{2}\) is the well-known LMS adaptation constant, i.e. the step size. Now that we have an update equation for the steering vector in the \(\theta\)’s look-direction, the only problem that remains is the expectation operator, which is not available at time update \(\ell\). Therefore, omitting it we finally have
\[
\hat{\mathbf{a}}_{\ell+1}(\theta) = \hat{\mathbf{a}}_\ell(\theta) + \mu \{p(\theta) - \hat{\mathbf{a}}_\ell^H(\theta) z_\ell\}^* z_\ell.
\]
A normalized LMS, i.e. NLMS, could also be proposed at this point to avoid sensitivities of the input norm, i.e. \(||z_\ell||\), which makes it extremely difficult to choose an adaptation constant for algorithm stability purposes [42]. To this end, the following update is proposed
\[
\hat{\mathbf{a}}_{\ell+1}(\theta) = \hat{\mathbf{a}}_\ell(\theta) + \mu \|z_\ell\|^2 \{p(\theta) - \hat{\mathbf{a}}_\ell^H(\theta) z_\ell\}^* z_\ell.
\]
Since \(\hat{\mathbf{a}}(\theta)\) also contains signal contributions present on direction \(\theta\), then a reasonable spectrum would be to measure the total power contained in the final estimate \(\hat{\mathbf{a}}_L(\theta)\), namely
\[
P(\theta) = ||\hat{\mathbf{a}}_L(\theta)||^2.
\]
Finally, the angles of arrival (AoAs) corresponding to the \(K\) targets are computed through a one-dimensional peak-finding search of \(P(\theta)\), viz.
\[
\Theta_{1:K}^{RIS} = \arg \max_{\theta_1, \ldots, \theta_K} P(\theta).
\]
A summary of an implementation of the proposed LMS filtering approach is summarized in Algorithm 1. One interesting feature of this batch approach is that it could be parallelized over angles to be evaluated on a grid, i.e. \(\Theta_{grid}\).

Algorithm 1 Batch NLMS filter Localization

- **INPUT** \(Z = [z_1 \ldots z_L]\), \(\mu, \Theta_{grid}\)
- while \(\theta \neq \emptyset\) do
  - \(\hat{\mathbf{a}}_0(\emptyset) \leftarrow 0_{N_{epoch} \times 1}\)
  - \(\ell \leftarrow 0\)
  - while \(\ell < L\) do
    - \(p(\ell) \leftarrow \mathbf{a}(H)^{H} H z_\ell\)
    - \(\hat{\mathbf{a}}_{\ell+1}(\theta) \leftarrow \hat{\mathbf{a}}_\ell(\theta) + \frac{\mu}{\|z_\ell\|} \{p(\theta) - \hat{\mathbf{a}}_\ell^H(\theta) z_\ell\}^* z_\ell\)
    - \(\ell \leftarrow \ell + 1\)
  - end while
  - if \(P(\theta)\) is peak then
    - Insert \(\theta\) in \(\Theta_{1:K}^{RIS}\)
  - end if
- return \(\Theta_{1:K}^{RIS}\)
Note that for peak detection, we first normalize the entire spectrum $P(\theta)$ so that its maximum value is 1. Then, we use MATLAB’s findpeaks() function to determine the peaks that exceed a certain threshold value, say $0 < \varphi < 1$.

Even though the implementation of Algorithm 1 is sequential over snapshot dimensions, i.e. over the columns of $Z$, one would have to wait for the entire samples to be received over epochs, i.e. the entire snapshot $z_t$ is needed so that the LMS algorithm can operate. In this context, a purely sequential approximated NLMS is proposed. The advantage of such an implementation is evident, i.e. an estimate of the different AoAs can be achieved per epoch.

**Algorithm 2** Sequential NLMS filter

**INPUT** $Z = [z_1 \ldots z_L]$, $\mu$, $\Theta_{grid}$

**INIT** $d_t(\theta) \leftarrow 0_{N_{grid} \times L}$, $P(\theta) \leftarrow 0_{N_{grid} \times 1}$

while $n = 1 \ldots N_{epoch}$ do

$\Theta_{RIS}^{1:K(n)} = \emptyset$

while $\theta \neq \emptyset$ do

$\ell \leftarrow 0$

while $\ell < L$ do

$d_t(\theta) \leftarrow d_t(\theta) + a^H(\theta) V_{n,\ell}^H Z_{n,\ell}$

$p \leftarrow p + \|Z_{n,\ell}\|^2 (d_t(\theta) - p^* Z_{n,\ell})^*Z_{n,\ell}$

$\ell \leftarrow \ell + 1$

end while

$P(\theta) \leftarrow P(\theta) + |p|^2$

Choose next $\theta \in \Theta_{grid}$

if $P(\theta)$ is peak then

Insert $\theta$ in $\Theta_{RIS}^{1:K}$

end if

end while

return $\Theta_{RIS}^{1:K}$

It is worth noting that for each epoch $n$, Algorithm 2 provides an estimate of the AoAs, i.e. $\Theta_{RIS}^{1:K(n)}$, as opposed to Algorithm 1 where we have to wait until the last epoch.

**VI. SIMULATION RESULTS**

In this section, we present different simulation results, conducted to illustrate the performance of the proposed methods. Furthermore, these methods are compared with a baseline, running the same methods depicted in Algorithm 1 and Algorithm 2 but without an RIS. Unless otherwise stated, we fix the number of epochs used for RIS measurements to $N_{epoch} = 100$. The number of time samples is set to $L = 100$ samples. Furthermore, the number of antenna elements at the PR is $N_{PR} = 8$ antennas. The threshold used for peak detection for both batch and sequential NLMS methods described in Algorithm 1 and Algorithm 2 is set to $\varphi = 0.5$. Moreover, we fix the angles between the AP and the RIS, and the RIS and the PR to $\theta_{AP} = -10^\circ$ and $\theta_{RIS} = -40^\circ$, respectively. A uniform linear array (ULA) configuration spaced at half a wavelength has been integrated at the PR.

In Fig. 2 we aim at analyzing the MSE as a function of SNR at the PR. The MSE is computed as

$$\text{MSE} = \frac{1}{PK} \sum_{k=1}^{K} \sum_{p=1}^{P} (\theta_k - \hat{\theta}_k)^2,$$  \hspace{1cm} (35)

The SNR at the PR is defined as

$$\text{SNR} = \frac{\mathbb{E}(|y_n^{(RIS)}(t) + y_n^{(AP)}(t) + \sum_{k=1}^{K} y_n^{(k)}(t)|^2)}{\mathbb{E}(|\epsilon_n(t)|^2)},$$ \hspace{1cm} (36)

where

$$y_n^{(RIS)}(t) = \rho_{RIS} \mathbf{a}(\theta_{RIS})^H \mathbf{x}(t) - \tau_{RIS},$$ \hspace{1cm} (37)

$$y_n^{(AP)}(t) = \rho_{AP} \mathbf{a}(\theta_{AP})^H s(t - \tau_{AP}),$$ \hspace{1cm} (38)

$$y_n^{(k)}(t) = \rho_{k} \mathbf{a}(\theta_{k})^H s(t - \tau_{k}).$$ \hspace{1cm} (39)

The parameter $\theta_k$ is the true AoA of the $k^{th}$ target and $\hat{\theta}_k$ is the estimated AoA of the $k^{th}$ target. We have simulated two
targets, i.e. $K = 2$. Also, $P$ is the number of Monte-carlo trials. We observe that at an MSE of 0.2 is achieved with the sequential NLMS method at SNR = $-18.55$ dB utilizing $M = 16$ reflective elements. The same MSE can be achieved at SNR = $-22.8$ dB with the batch NLMS method, translating to a gain of 4.25 dB. Comparing both methods to the no-RIS baseline, a gain superior to 20 dB can be attained. This demonstrates the advantage of the proposed RIS-aided model, as the accuracy of the AoA estimates are drastically improved.

On the other hand, since the proposed methods also offer joint detection of number of targets, we also study the probability of correct detection for the proposed methods.

In Fig. 6, we study the probability of correct detection of the proposed methods, and compare it with the baseline scheme. The detection probability is computed as follows

$$P_D = \frac{\text{no. of correct target enumeration}}{\text{no. of trials}}. \quad (40)$$

Setting a level of $P_D = 0.9$, and when no RIS is deployed, the required SNR is SNR = $-4.4$ dB for batch NLMS, as opposed to SNR = 0.95 dB for sequential NLMS. A gain of 16 dB in terms of SNR is noticed, when using an RIS with only $M = 16$ reflective elements. An additional 4 dB gain can be attained when doubling the number of RIS reflective elements.

To get a better sense of target localization accuracy, we study the SRP in Fig. 4. To this end, the SRP is defined as follows

$$\text{SRP} = \frac{\text{no. of trials with all } \theta_k = \hat{\theta}_k}{\text{no. of trials}}. \quad (41)$$

As it can be concluded, the non-aided RIS scenario cannot achieve a perfect SRP with $L = 100$ time samples and $N_{PR} = 8$ antenna elements. The SRP is saturated in this case at 66% starting at SNR = 16 dB. In contrast, we observe that 66% SRP can be achieved with SNR = $-8$ dB with only $M = 16$ reflective elements. Furthermore, and by doubling the number of reflective elements, we can achieve an additional
of resolvable targets to \(M\). We can further double the number with a second approach with an MSE of \(M = 32\) reflective elements. Comparing this baseline scheme with an RIS-aided scenario with \(M = 32\) reflective elements, where for the same \(P_D\), the angular separation is improved by a factor of 2.25, i.e. \(\Delta = 4^\circ\). This resolution can even be improved towards \(\Delta = 2.3^\circ\) for the same \(P_D\), just by doubling the amount of reflective elements.

Fig. 9 shows the spectra obtained by the proposed NLMS filtering methods, namely Fig. 9a shows the spectrum of Algorithm 1 whereas Fig. 9b shows that of Algorithm 2. It is clear from both simulations that the peaks are sharp enough to successfully resolve the \(K = 4\) targets. Notice that for the sequential NLMS filter, we remind the reader that Algorithm 2 yields a spectrum \(P(\theta)\) per epoch. Naturally, the spectrum starts off with peaks that skew from their true positions, resulting in a poor resolution. Nevertheless, with increasing epoch number, the spectrum smooths down and peaks converge to their true positions.

VII. CONCLUSIONS AND FUTURE INSIGHTS

In this manuscript, target localization in terms of AoA is accomplished via a newly proposed architecture well-suited for communication-centric ISAC designs, consisting of an RIS and monitored by a PR, where target detection and estimation are performed. Towards such a setting, we posit an optimization framework enabling us to configure the phase shifters at the RIS in order to reliably mirror the useful reflections caused by the intended targets. Furthermore, we have derived two methods, motivated by the problem of minimal information available at the disposal of the PR. These methods are based on the NLMS filter, and are well-suited for joint detection of number of targets and estimation of the AoAs of the corresponding targets within the proposed RIS-aided communication-centric ISAC architecture. Numerical simulations validate the superior performance of both methods, when applied on the proposed architecture.

Future work will be oriented towards an adaptive beamformer, where the goal would be to learn the covariance matrix of the interference plus noise part, thanks to the target localization part, which could leverage such necessary information for covariance construction. Moreover, further extensions towards more sophisticated infrastructure, such as simultaneous AP transmissions or hybrid RIS where the goal would be to guarantee a reflected signal with good communications and radar characteristics. Furthermore, one could exploit additional sensing parameters with our proposed scenario, such as distance estimation via propagation delays and velocity estimation via doppler information. Also, one could generalize the scenario at hand toward two-dimensional and three-dimensional localization, by exploiting azimuth-elevation information. Even more, multiple RIS could be deployed, therefore, the PR would create multiple beams to align
its look direction at those surfaces. A generalization of the aforementioned direction is to have each RIS oriented towards possibly different objectives, i.e., sensing, communication, and security. Future research will also be shifted towards a deeper analysis oriented towards fundamental limits of the proposed model, i.e. Cramér-Rao bound analysis. This could allow to determine the required number of reflective RIS elements required for a given positioning accuracy.

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