COLoRIS: Localization-agnostic Smart Surfaces Enabling Opportunistic ISAC in 6G Networks

Guillermo Encinas-Lago, *Student Member, IEEE,* Francesco Devoti, *Member, IEEE,* Marco Rossanese, *Student Member, IEEE,* Vincenzo Sciancalepore, *Senior Member, IEEE,* Marco Di Renzo, *Fellow, IEEE,* Xavier Costa-Pérez, *Senior Member, IEEE,*

Abstract—The integration of Smart Surfaces in 6G communication networks, also dubbed as Reconfigurable Intelligent Surfaces (RISs), is a promising paradigm change gaining significant attention given its disruptive features. RISs are a key enabler in the realm of 6G Integrated Sensing and Communication (ISAC) systems where novel services can be offered together with the future mobile networks communication capabilities. This paper addresses the critical challenge of precisely localizing users within a communication network by leveraging the controlled-reflective properties of RIS elements without relying on more power-hungry traditional methods, e.g., GPS, adverting the need of deploying additional infrastructure and even avoiding interfering with communication efforts. Moreover, we go one step beyond: we build COLoRIS, an *Opportunistic ISAC* approach that leverages localization-agnostic RIS configurations to accurately position mobile users via trained learning models. Extensive experimental validation and simulations in large-scale synthetic scenarios show **5%** positioning errors (with respect to field size) under different conditions. Further, we show that a low-complexity version running in a limited off-the-shelf (embedded, low-power) system achieves positioning errors in the **11%** range at a negligible **+2%** energy expense with respect to the classical RIS.

Index Terms—Localization, Reconfigurable intelligent surfaces, Deep learning, Integrated sensing and communication

1 Introduction

In the ever-evolving landscape of modern technology, the implementation of emerging technology, such as Reconfigurable Intelligent Surfaces (RISs),[1] has emerged as a transformative force, reshaping the way we perceive and interact with the propagation environment [?]. RIS allows directly controlling how electromagnetic waves propagate throughout the environment, opening up to never-explored use-cases.

The merger of the sensing sphere with the communications world engenders the novel concept of Integrated Sensing and Communication (ISAC) [?]. ISAC represents a cutting-edge paradigm that heralds an era of interconnectedness and data-driven decision-making: At the heart of this evolution are smart surfaces, which act as key enablers, unleashing the full potential of ISAC applications. This holistic approach empowers systems not only to transmit and receive data, but also to collect, process, and utilize it for a wide array of applications, such as localization, detection, etc. [?]. ISAC's domain spans from smart cities and industrial automation to healthcare and environmental monitoring, offering solutions that are not only more efficient but also more environmentally sustainable. Nevertheless, the integration of such components presents a multitude of intricate challenges that pose a substantial threat to the overall system stability. The network infrastructure that is currently deployed may necessitate a sophisticated orchestration and management framework in order to extend its functionality for data acquisition [?], while still serving its conventional communication purposes.

This calls for a compelling transition of the preexisting network equipment towards a novel and frictionless utilization, which inherently supports the extraction of contextual information for sophisticated machine learning models capable of capturing and deducing sensory data, going beyond the RIS-based passive radar applications [?] or Simultaneous Localization and Mapping (SLAM) techniques [?]. This innovative paradigm can be termed as *opportunistic ISAC* as it seamlessly capitalizes on the wireless network configurations to infer pertinent positioning information accurately. Unlike most localization systems leveraging RIS, our method does not interfere with the overall communication operations. In particular, we do not alter how the RIS is used, configured, or optimized. Indeed, we only rely on the available (selected) RIS configuration information for communication to eventually perform localization in a seamless manner. Conversely, existing localization techniques with RIS require specific operations, e.g., time blocks exclusively devoted to localization [?], dedicated configurations [?], configuration sweeps [?], etc., done *ex-professo* to locate the user, that harm communication performance and compatibility with existing equipment. This not only sets a new benchmark in efficiency by requiring significantly less power and computational resources, thereby heralding a sustainable and cost-effective approach. But it also underscores the limitations of traditional analytical models, which often remain intractable when compared to the flexibility and scalability of machine learning-based methodologies.

Within this context, we pioneer a novel Machine Learning (ML)-based framework, namely *Configuration-based Opportunis-*

Guillermo Encinas-Lago is with NEC Laboratories Europe, 69115 Heidelberg, Germany and Université Paris-Saclay, CNRS, CentraleSupélec, Laboratoire des Signaux et Systèmes, 91190 Gif-sur-Yvette, France. Francesco Devoti, Marco Rossanese and Vincenzo Sciancalepore are with NEC Laboratories Europe. Marco Di Renzo is with Université Paris-Saclay, CNRS, CentraleSupélec, Laboratoire des Signaux et Systèmes. Xavier Costa-Pérez is with i2cat, ICREA, 08034 Barcelona, Spain and NEC Laboratories Europe. *This work was supported by the EU SNS JU INSTINCT project under grant agreement no. 101139161.*
Email of the corresponding author: Guillermo.Encinas@neclab.eu.

[1]Note that the terms RIS and Smart Surface can be used interchangeably within the paper, as they refer to the same physical device.

tic Localization via RIS (COLoRIS), which harnesses successive RIS configurations, primarily focused on augmenting the overall system communication capabilities, to forecast exact user positions.

Contributions. To summarize, we *(C1)* introduce a novel opportunistic ISAC framework that exploits RIS configurations seamlessly, *(C2)* propose a metric for the accuracy achievable in such a framework by formulating a Fisher Information (FI)-based metric, treating RIS as a phase measurement device, *(C3)* confirm the feasibility of our proposal and obtain its maximal achievable performance by evaluating RIS configurations in practical scenarios, *(C4)* prove the practical feasibility of our framework by implementing a ML-based architecture able to locate users with sub-meter accuracy, *(C5)* incorporate and test an error prediction engine, *(C6)* propose a complexity reduction strategy based on the FI of the individual RIS element and showcase its performance, *(C7)* develop and prototype COLoRIS using off-the-shelf devices and validate our proposal in a low-cost, low-power embedded ARM-based architecture connected to a commercial RIS device, *(C8)* confirm via power measurements that COLoRIS can function using a fraction of the available power from RIS-based energy harvesting sources, and can operate for more than a year on a CR2032 coin battery while doing tens of thousands of position measurements per day.

Notation. Matrices are in bold capital letters ($\mathbf{X}$), vectors are in small capital letters ($\mathbf{x}$), and scalars are in small letters (x). $\angle(\cdot)$ denotes the unary angle operator. The n-th element of the vector $\mathbf{x}$ is denoted as $\{\mathbf{x}\}_n$. Similarly, the m-th column of the matrix $\mathbf{X}$ is denoted as $\{\mathbf{X}\}_m$. The transpose, the Hermitian, and the trace of the matrix $\mathbf{X}$ are denoted as $\mathbf{X}^{\mathrm{T}}$, $\mathbf{X}^{\mathrm{H}}$, and $\mathrm{tr}(\mathbf{X})$, respectively. The norm of a vector $\mathbf{x}$ is $\|\mathbf{x}\|$. The gradient operator with respect to the $N \times 1$ vector $\mathbf{x}$ is $\nabla_{\mathbf{x}} = [\frac{\partial}{\partial x_1}, \dots, \frac{\partial}{\partial x_N}]^{\mathrm{T}}$. The expected value of a function $f(Z)$ is $\mathbb{E}\left[f(Z)\right]$, and the average of a quantity x is denoted as $\overline{x}$. Sets are in calligraphic uppercase letters ($\mathcal{X}$), and their cardinality is denoted as $|\mathcal{X}|$.

2 Analysis

We consider a reference scenario as depicted in Fig. 1 with a RIS deployed within the service area of a Base Station (BS) with M antennas serving a single antenna User Equipment (UE). The RIS comprises $N = N_y N_z$ elements distributed as an Uniform Planar Array (UPA) lying on the yz-plane, where N_y and N_z are the number of elements on the y- and the z-axis, respectively. The BS and the RIS antenna arrays are centered in $\mathbf{b}$, and $\mathbf{r}$, respectively, while the antenna of the UE is centered in $\mathbf{u}$. The corresponding Multiple-Input Single-Output (MISO) channel is defined as follows

$$\mathbf{h}^{\mathrm{H}} \triangleq \mathbf{h}_{RU}^{\mathrm{H}} \mathbf{\Theta}^{\mathrm{H}} \mathbf{H}_{RB} + \mathbf{h}_{D}^{\mathrm{H}} \in \mathbb{C}^{M \times 1}, \tag{1}$$

with $\mathbf{h}_D \in \mathbb{C}^{M\times 1}$ denoting the direct BS-UE channel, $\mathbf{H}_{RB} \in \mathbb{C}^{N\times M}$ and $\mathbf{h}_{RU} \in \mathbb{C}^{N\times 1}$ corresponding to the RIS-BS and the RIS-UEs paths, respectively, and $\mathbf{\Theta} \in \mathbb{C}^{N\times N}$ is the RIS configuration that is described in its most generic form as

$$\mathrm{diag}(\mathbf{\Theta}) = [\alpha_1 e^{j\theta_1}, \dots, \alpha_N e^{j\theta_N}]^{\mathrm{T}}, \tag{2}$$

where $\alpha_n \in [0,1]$ and $\theta_n \in [0, 2\pi)$ are the gain and the phase shift of the n-th element of the RIS, respectively. We consider the RIS device to be capable of phase modifications i.e., $\alpha_n = 1 \; \forall \; n = 1, \dots, N$, and $\mathrm{diag}(\mathbf{\Theta}) = [e^{j\theta_1}, \dots, e^{j\theta_N}]^{\mathrm{T}}$.

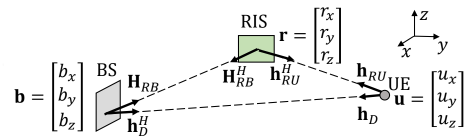

Fig. 1. Geometrical representation of the considered scenario, including the BS position $\mathbf{b}$, the RIS position $\mathbf{r}$, and a UE position $\mathbf{u}$.

We denote the RIS array response with the vector $\mathbf{a}_R(\mathbf{p}) \in \mathbb{C}^{N\times 1}$ with elements defined as the following

$$\{\mathbf{a}_R(\mathbf{p})\}_n^N \triangleq G(\mathbf{p}) e^{-\jmath \frac{2\pi}{\lambda}(\|\mathbf{p}-\mathbf{q}_n\| - \|\mathbf{p}-\mathbf{p}_{\text{ref}}\|)}, \tag{3}$$

where $\mathbf{p} \in \mathbb{R}^3$ is the point of departure or arrival of the signal, λ is the wavelength at the carrier frequency f_0, $\mathbf{q}_n = \mathbf{p}_n - \mathbf{p}_{\text{ref}} \in \mathbb{R}^3$ is the offset between the absolute position $\mathbf{p}_n$ of the n-th RIS element and the arbitrary RIS reference point $\mathbf{p}_{\text{ref}} \in \mathbb{R}^3$, and $G(\mathbf{p})$ is the gain of the element in the direction of $\mathbf{p}$, which is $G(\mathbf{p}) = 1$ under the assumption of patch antenna elements.

Importantly, Eq. (3) accounts for the wavefront curvature at the RIS as it depends directly on the location $\mathbf{p}$, rather than on angles of arrival and departure only [**?**], [**?**]. The BS array response vector $\mathbf{a}_B(\boldsymbol{p}) \in \mathbb{C}^{M\times 1}$ is defined similarly.

Having defined the array steering vectors, we can now define the channels $\mathbf{H}_{RB}$, $\mathbf{h}_{RU}$, and $\mathbf{h}_D$ as follows

$$\{\{\mathbf{H}_{RB}\}_m^M\}_n^N \triangleq \sqrt{\gamma(\mathbf{p}_n, \mathbf{p}_m)}\{\mathbf{a}_R(\mathbf{p}_m)\}_n \{\mathbf{a}_B^{\mathrm{H}}(\mathbf{p}_n)\}_m, \tag{4}$$

$$\{\mathbf{h}_{RU}\}_n^N \triangleq \sqrt{\gamma(\mathbf{p}_n, \mathbf{u})}\{\mathbf{a}_R(\mathbf{u})\}_n, \tag{5}$$

$$\{\mathbf{h}_{D}\}_m^M \triangleq \sqrt{\gamma(\mathbf{p}_m, \mathbf{u})}\{\mathbf{a}_B(\mathbf{u})\}_m, \tag{6}$$

where $\gamma(\mathbf{x}, \mathbf{y})$ is the path gain between two given locations $\mathbf{x}$, $\mathbf{y} \in \mathbb{R}^3$ and is defined as the following

$$\gamma(\mathbf{x}, \mathbf{y}) \triangleq \gamma_0 \left(\frac{d_0}{\|\mathbf{x}-\mathbf{y}\|}\right)^{\beta}, \tag{7}$$

where γ_0 is the channel power gain at a reference distance d_0 and β is the pathloss exponent.

We consider a generic, non-ideal, channel estimation process that returns the estimation of $\hat{\mathbf{H}}_{RB}$, $\hat{\mathbf{h}}_{RU}$, and $\hat{\mathbf{h}}_D$ as Channel State Information (CSI).

Moreover, we assume the presence of a phase selection agent that optimizes the RIS configuration based on the available CSI. To ease the notation, we introduce an alternative but equivalent representation of $\mathbf{\Theta}$ with the definition of the following vector

$$\boldsymbol{\theta} = \mathrm{diag}(\angle\mathbf{\Theta}) = [\theta_1, \theta_2, \dots, \theta_N]^{\mathrm{T}} \in \{0, 2\pi\}^{N\times 1}. \tag{8}$$

We denote the selected RIS configuration as $\bar{\boldsymbol{\theta}}$, and we describe the optimization process executed by the agent as

$$\bar{\boldsymbol{\theta}} = \angle\bar{\mathbf{\Theta}} = g(\hat{\mathbf{H}}_{RB}, \hat{\mathbf{h}}_{RU}, \hat{\mathbf{h}}_D) = \underbrace{g(\mathbf{H}_{RB}, \mathbf{h}_{RU}, \mathbf{h}_D)}_{\boldsymbol{\theta}^*} + \mathbf{e}_{\boldsymbol{\theta}}, \tag{9}$$

where $g(\cdot)$ is the RIS configuration optimization process, $\boldsymbol{\theta}^*$ is the optimal configuration obtained when perfect CSI is available, and $\mathbf{e}_{\boldsymbol{\theta}}$ is the error introduced by the non-ideal channel estimation process. Note that phase shift values can be either discrete or continuous, depending on the RIS design [**?**], [**?**]. We characterize $\bar{\boldsymbol{\theta}}$ in the continuous case, and face the discrete case later in this section.

In its most general form—as detailed in Section 2.1—the configuring agent operates as a phase measurement device that extracts the phase of the CSI. Given the direct dependence of

CSI quality on the Signal to Noise Ratio (SNR),[2] we assume the spread of the error $\mathbf{e}_\theta$ to be inversely proportional to the SNR.

Furthermore, for the sake of tractability and without loss of generality, we assume phase measurements to be independent at each RIS element. Hence, we model the error $\mathbf{e}_\Theta$ as a normal Random Variable (RV) with distribution $\mathbf{e}_\theta \sim \mathcal{N}(\mathbf{0}_N, \sigma_\theta^2 \mathbf{I}_N)$, with $\sigma_\theta^2 = \frac{1}{2\gamma}$, where γ denotes the SNR.

Accordingly, $\bar{\theta}$ is a normal RV with distribution

$$\bar{\theta} \sim f_{\bar{\theta}}(\bar{\theta}) = \mathcal{N}(\theta^*, \sigma_\theta^2 \mathbf{I}_N). \tag{10}$$

Section **??** provides a formal demonstration of Eq. (10).

When considering an RIS hardware capable of discrete phase shifts, we assume the set of feasible configurations

$$\mathcal{Q} = \left\{ \Delta m : m = 0, \ldots, 2^{Q-1}, m \in \mathbb{N} \right\}, \tag{11}$$

where Q denotes the phase shifts quantization level, and $\Delta = \frac{2\pi}{2^Q}$. The total number of feasible configurations is $|\mathcal{Q}| = 2^Q$. Phase shifts are set according to the quantization function $q : \mathbb{R} \to \mathcal{Q}$ defined as

$$q(x) = \Delta \left\lfloor \frac{x}{\Delta} + \frac{1}{2} \right\rfloor. \tag{12}$$

The quantized RIS configuration is obtained as $\bar{\theta}_Q = q(\bar{\theta})$. Again, $\bar{\theta}_Q$ is a RV, which is distributed as the following

$$\bar{\theta}_Q \sim f_{\bar{\theta}_Q}(\bar{\theta}_Q) = \prod_{n=1}^{N} f_{\bar{\theta}_{Q,n}}(\bar{\theta}_{Q,n}), \tag{13}$$

with

$$f_{\bar{\theta}_{Q,n}}(\bar{\theta}_{Q,n}) = \sum_{m=0}^{2^{Q-1}} P\left(\bar{\theta}_{Q,n} = \Delta m\right) \delta\left(\bar{\theta}_{Q,n} - \frac{2\pi}{2^Q} m\right), \tag{14}$$

where $\delta(\cdot)$ is the delta function, and

$$P\left(\bar{\theta}_{Q,n} = \Delta m\right) = \int_{\Delta(m-0.5)}^{\Delta(m+0.5)} f_{\bar{\theta}_n}(\theta) d\theta \tag{15}$$

is the probability of selecting $\bar{\theta}_{Q,n} = \Delta m$.

2.1 Optimizing RIS Configurations

The RIS configuration process is generally complex, as it implies the joint optimization of the BS precoder and the RIS configuration to maximize a given objective Key Performance Indicators (KPIs), and is currently still an open problem [**?**]. Hereafter, we summarize the main joint optimization strategies: $i)$ *Gradient optimization*: iterative adjustment of RIS configuration and BS to optimize given metrics (e.g., SNR) in the direction of the gradient; $ii)$ *Alternating optimization*: optimization of each independent subproblem while keeping the other fixed [**?**], [**?**]; $iii)$ *Machine Learning*: application of ML agents to face RIS configuration problems [**?**], [**?**]; $iv)$ *Coherent paths*: a practical approach that maximizes the gain of the reflected path while achieving constructive interference with the direct path [**?**].

Considering the coherent paths configuration solution, the RIS configuration process $g(\cdot)$ can be written in a closed form while still obtaining results comparable to more complex optimization procedures [**?**]. We anticipate that this optimization approach enables us to create offline ground-truth data that we use for training COLoRIS, as described in Section **??**.

[2]CSI estimation techniques (as pilot signals) are impacted by SNR: higher SNR improves accuracy and vice versa ([**?**]).

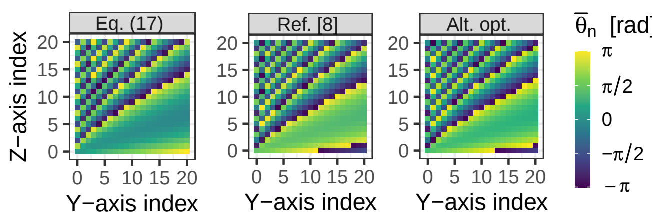

Fig. 2. RIS configurations from coherent paths optimization Eq. (**??**), optimization method from [**?**] and alternate optimization algorithm from [**?**].