A Novel 3D Object Classification Paradigm through Reconfigurable Intelligent Surfaces

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***Abstract*—Programmable Wireless Environments (PWEs) leverage Reconfigurable Intelligent Surfaces (RIS) to convert the wireless propagation into a deterministic process. Recently, PWEs have shown promising results in boosting the efficiency of Radio-Frequency (RF) imaging, creating a novel, lightweight object detection and visualization approach for Extended Reality (XR). As a first step towards optimizing the PWE-XR synergy, this work proposes and compares a set of four PWE configuration policies. The goal is to deduce which policy yields the optimal classification of a set of arbitrary 3D objects present within the PWE. The rationale is that the PWE configuration policy that yields optimal object classification, will also yield the best XR quality in subsequent studies. Evaluation results regarding the performance of the proposed policies, based on ray-tracing, are demonstrated and discussed.**

***Index Terms*—Metasurfaces, reconfigurable intelligent surfaces (RIS), wireless, imaging, robotics, vision, XR.**

I. Introduction

Over the last few years, RISs have emerged as a significant topic in recent wireless propagation research due to their unique capabilities [1], [2]. Specifically, RISs have the unique ability to interact with an impinging wave in a software-defined manner, can steer it in any desired direction, modify its phase, polarization, or even absorb it entirely. Building upon this, when multiple RIS units are orchestrated in coordination under a centralized server, we can efficiently construct a PWE [1]. Within this environment, there's an opportunity to exert near-complete control over wireless propagation. Such control can minimize interference, combat Doppler and fading effects, and enhance security against eavesdroppers. This has led to PWEs capturing significant attention in wireless communications research, especially in the quest for configurations that optimally assist futuristic applications based on wireless propagation [1], [2].

Furthering this exploration, there's an increasing interest in leveraging the capabilities of PWE to enhance RF imaging for applications including cost-effective robotic vision [3], [4], [5]. RF imaging, distinctively, utilizes microwave sources to detect objects and shapes, bypassing the traditional visible light mechanisms[3]. Furthermore, the precision and depth of 3D object classification become paramount in this context, offering a richer understanding of the environment and enhancing the potential applications of RF imaging. However, the possible synergy between PWE and RF imaging brings forth a pivotal question: *Is it feasible to amplify the performance of an RF imaging system by optimally utilizing a PWE for wireless propagation between the RF imaging source and the wavefront reader?*

Given the immense potential of melding PWE with RF-Imaging, particularly in the domain of extended reality (XR) applications [4], this paper sets out to understand PWE configurations tailored for RF-driven XR, known as XR-RF. First, we remark that existing XR-RF requires the time-consuming training of neural network, which handles the translation of RF wavefronts into actual graphics. Thus, it is not practical to study the PWE optimization using metrics of graphics as the optimization driven. Instead, we study the PWE component separately, and seek to configure it to optimally classify arbitrary 3D objects within it. The assumption is that such a PWE policy will also benefit the quality XR-RF graphics in future studies. We propose four PWE configuration policies, examining their impact on object classification within a PWE-centric RF-Imaging framework and evaluating their performance metrics.

The remainder of the paper is organized as follows. Section II presents related studies and prerequisites for the considered system model. Section III presents the proposed PWE configuration policies for 3D object detection. Section IV presents the evaluation via simulations and the paper is concluded in Section V.

II. Background and System Model

Related Work. RF-Imaging technology has seen a plethora of research approaches [6], [7]. In all efforts, the inherently stochastic nature of wireless communication channels remains a consistent challenge. Recent explorations have delved into the potential of RIS to enhance RF-Imaging. These investigations primarily focus on smart radio environments (SREs) [5], characterized by environments with a *single* RIS that can execute specific functions on impinging electromagnetic waves.

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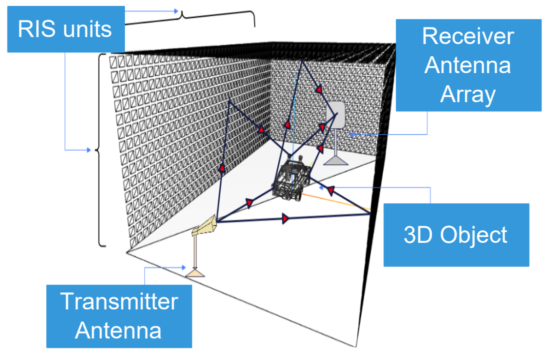

Fig. 1. Schematic of the system model.

However, this approach does not exploit the transformative potential of PWEs, which envision wireless propagation as a software-defined, deterministic procedure.

The authors' previous work, [4], projects the incorporation of RISs into the 5G/6G infrastructure, positioning them as pivotal components of PWEs. Such an integration could significantly amplify the capabilities of XR-RF applications, paving the way for innovative, low-cost and minimal-latency solutions. This potential stems from the direct translation of electromagnetic wavefronts into graphics directly, without relying on 3D object positioning devices, such as sensors and gyroscopes. The confluence of PWE and RF Imaging is set to tackle prevailing challenges in the extended reality sphere. Inspired by this perspective, our current work delves into the performance of various PWE configurations in the context of an object classification paradigm.

System Model. Fig. 1 depicts the schematic of our proposed system design set in an indoor environment. Here, an arbitrary 3D object is centrally positioned, and a transmitter antenna emits a single-tone signal. The scattered wavefront, which corresponds to each unique object, is then captured by the receiver antenna array.

Our study centers on the software-defined control of wireless propagation. The primary goal is to receive electromagnetic information that most accurately corresponds to each object. We achieve this by employing PWE technology, which involves covering the room's surfaces, including walls and ceilings, with RIS units [1]. Each RIS unit is capable of executing various electromagnetic functions like wave reflection in user-defined directions, absorption, or phase and polarization modification. Our primary emphasis in this study is on reflecting incoming waves in specific directions. Through precise control of each RIS's response and manipulation of scattered wave propagation paths, we intend to create a wireless environment that possesses a nearly unique signature, representing the distinct electromagnetic characteristics of individual objects.

III. The Proposed PWE Configuration Policies for 3D Object Classification

Workflow and PWE Configurations. We proceed by describing the overall system workflow, in order to convey the role of the proposed PWE configuration policies for 3D Object Classification. In essence, the process leverages the PWE technology to discern and classify objects based on their electromagnetic interactions and consists of four steps as follows:

1) Position an object at the center of a room, directing the main lobe of the transmitter antenna towards it.
2) Harness the capabilities of PWE technology to manipulate the EM wave propagation.
3) Analyze the resulting propagation phenomenon to extract salient features.
4) Employ a classification model trained on these features to predict the object present in the room based on the received wavefront.

Each RIS in the PWE adjusts its EM response behavior based on instructions from a central server. This process is termed a complete PWE configuration.

While [4] suggests training a GAN model for evaluating the graphics of the XR-RF, constraints of time and energy make training a simpler classification model, as in step 4 above, a more feasible approach for evaluating PWE configurations for XR-RF. This model classifies objects in the room based on features from the EM wavefront at the Rx antenna, shaped by the unique attributes of objects and the PWE configuration.

RISs offer a plethora of functionalities, resulting in diverse PWE configurations. To this end, it is essential to evaluate the performance across these configurations to discern disparities and derive insights. The static configurations, where RISs have a set response, primarily focus on directing the impinging EM wave. The aim of PWE configuration is to design propagation routes that aptly describe an object's geometry, enriching the dataset for the machine learning classification model.

Proposed configuration policies. The efficiency of any PWE-driven system largely hinges on the configuration policies employed. In our study, we examine four distinct configurations, each tailored to a specific propagation strategy, ensuring a comprehensive evaluation of potential PWE behaviors:

- **MultiPathConf**: Here, the RISs act as reflectors towards a random direction, up to a fixed number of total reflections. The last RIS sends the impinging wave to the receiver. The goal is to force the waves to follow paths of random total length before reaching the receiver..
- **RxFocusConf**: This configuration emphasizes directing radiation towards the receiver antenna (Rx). Each RIS unit, depending on its placement on a wall or ceiling, aims to channel the radiation scattered from the corresponding side of the object directly to the antenna array receiver.
- **ObjFocusConf**: The primary objective here is to maximize the RF illumination of the object. RISs units on each side wall or ceiling redirect incoming radiation

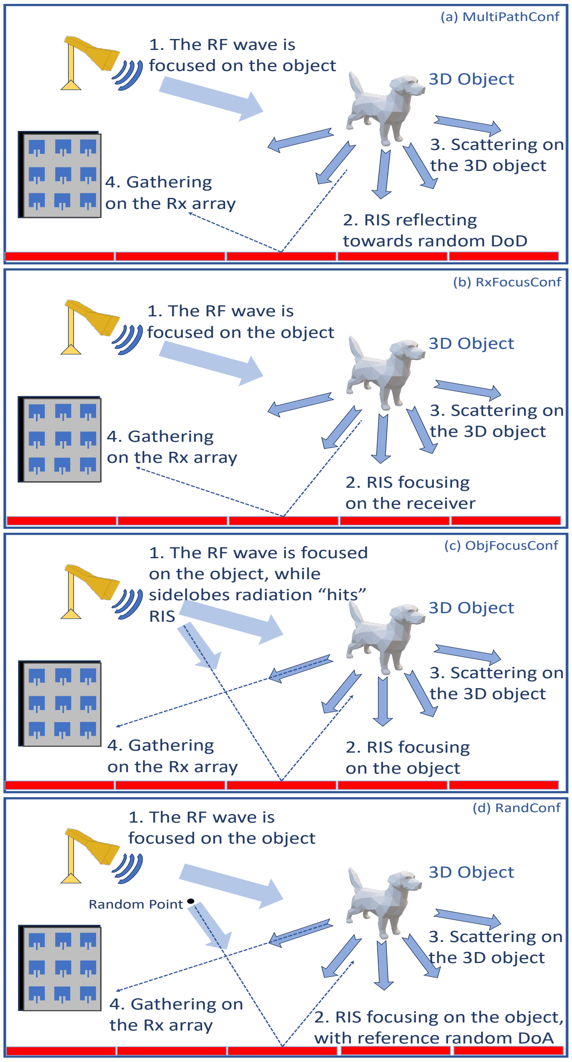

Fig. 2. Indicative examples of the studied PWE configuration policies. RIS units are illustrated on the bottom wall only for clarity.

towards the corresponding side of the object. The Tx-antenna serves as a reference, ensuring radiation from the transmitter is optimally redirected to illuminate the object.

- **RandConf**: Similar in intent to ObjFocusConf, this configuration seeks to enhance the RF illumination of the 3D object. The distinction lies in the direction of arrival of the impinging wave to the RISs, which is from a set of random points (uniformly distributed) on the opposite side of the room from where the RISs are situated.

Simple examples of each configuration are illustrated in Fig. 2. Each of these configurations offers a unique approach to manipulating electromagnetic wave propagation, making their comparative analysis crucial for a holistic understanding of PWE's potential.

To elucidate the PWE Configuration Policies, we delve deeper into the *ObjFocusConf* configuration. This choice facilitates a clearer understanding of the system's operation. Figure 3 illustrates the RIS units arrangement and the propagating EM wave within the environment, showcasing three representative routes.

Each RIS is pre-configured to reflect the incoming wave based on a specific angle of arrival, directing it towards a predetermined direction. This is achieved by programming the metasurface with the function *steer(angle of arrival, angle of departure)*. Given that the objects under study share similar dimensions, we employ an imaginary sphere encompassing each object. This sphere aids in defining the angles of departure for each RIS setup. Uniformly selected points on the sphere's surface determine the desired *angle of departure* for each RIS unit. The angle of departure for a RIS is defined by the angle between the wall's normal vector, which the RIS unit covers, and the line segment connecting the RIS's center to a point on the sphere's surface. Conversely, the angle of arrival is determined by the angle between the wall's normal vector and the line segment connecting the RIS's center to the transmitter antenna.

It's pivotal to note that the RIS functionality remains static throughout the propagation. Hence, waves arriving at the RIS from angles different from the predefined one result in varied angles of departure for the reflected wave. The figure illustrates this:

- In Route 1 (red), a ray from the Tx antenna reflects off a right-wall RIS, impinges upon the object, and then scatters to an upper-right corner RIS. This RIS, originally programmed to reflect rays from the Tx towards the object, redirects the ray to the Rx due to the altered angle of arrival.
- Route 2 (green) sees a ray redirected by a back-wall RIS to re-illuminate the object, which then scatters it towards the receiver.
- Route 3 (orange) demonstrates a ray impinging upon the object, scattering towards a RIS, which then reflects it based on its programmed direction, but not necessarily back to the object due to a differing angle of arrival. The primary objective of this PWE configuration is to enhance the RF illumination of the object, capturing richer geometric information, thereby bolstering classification accuracy.

In summary, these four PWE configurations are chosen to be examined because of their basic exertion of control over the EM wave propagation in the wireless environment. Despite the basic manipulation what is of importance is the insight that can be obtained about what is the correct way of approaching the problem of the EM wave routing which is not obvious in the beginning.

IV. Evaluation

In this section, we detail the evaluation of our proof-of-concept test and present the classification outcomes. Our experimental setup involves a standard cuboid room with dimensions width = 5m, length = 8.5m, and height = 3m. Within this space, we centrally position one of three objects: i) **a bust**, ii) **a car**, and iii) **a dog**, as depicted in Fig 3. A horn

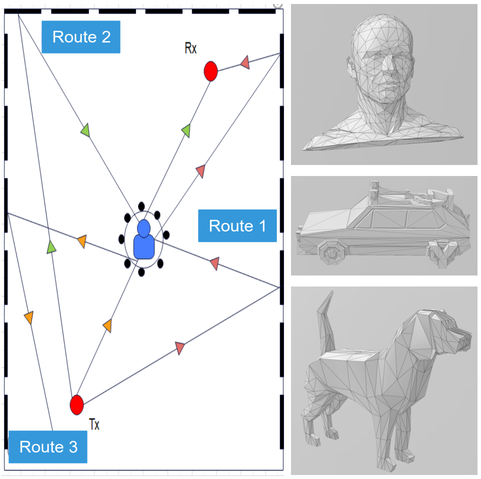

Fig. 3. Configuration Example according to the proposed *ObjFocusConf* policy. The 3D objects considered in the evaluation are shown to the right.

transmitter antenna, with a 20dBi directivity, is situated at (1, 2.5, 1.5) and is oriented towards the object. Additionally, an antenna array receiver (32×32 with inter-element distances of $\lambda/2 \times \lambda/2$) is placed at (0, -3.5, 1.5). The system operates at a frequency of 10GHz. The room's walls and ceiling are coated with square-shaped RISs, each measuring 0.15m×0.15m, with a consistent gap of 0.05m between adjacent RISs.

Our methodology employs ray-tracing simulations, wherein each object undergoes 70 distinct rotations around a randomly chosen axis, forming our dataset. This dataset is partitioned into a 0.75-0.25 (train-test) split, with the training phase incorporating a 5-fold cross-validation.

The ray-tracer that is used is the Matlab's implementation, based on the SBR method with the number of reflections set to four and number of diffractions set to one. The output is a ray object containing information about the wireless propagation (e.g. attenuation, phase change, etc.). The classification algorithm that is employed is the XGBoost, which later undergoes hyper-parameter tuning.

The dataset's formation is as follows: The transmitted signal is defined as $x = Acos(2\pi f t)$. Given its bandwidth, the resultant equivalent baseband signal at the receiver antenna is expressed as $r_l(t) = a_i e^{-j\phi_i} s_l(t)$, where the wireless channel is modeled as a complex number $h_i = a_i e^{-j\phi_i}$. It's evident that the variance in each received signal $(r_l(t))$ is encapsulated within the channel information. By capturing the amplitude attenuation and phase change for each distinct wireless channel route, we formulate two random variable (RV) vectors: amplitude attenuation ($\mathbf{A}$) and phase change (Φ). The feature vector is subsequently derived by computing the four primary moments of each RV.

To assess the performance of each proposed PWE configuration policy, we summarize their standard classification metrics (accuracy, precision, recall, F1 score [8]) in Table I.

Out of the four compared policies, *MultiPathConf* performs best in total, with an F1 score of 0.807. Here, we remark

TABLE I
CLASSIFICATION SCORES OF THE PROPOSED CONFIGURATIONS.

Policy	Accuracy	Precision	Recall	F1 score
MultiPathConf	0.811	0.814	0.811	0.807
RxFocusConf	0.566	0.581	0.566	0.569
ObjFocusConf	0.736	0.739	0.736	0.736
RandConf	0.585	0.585	0.585	0.585

that *MultiPathConf* attempts to capture the 3D object traits in the phase of received wavefront. In particular, it creates a static, random-phase wavefront that is perturbed by each 3D object. This is indicated to result in a scheme that encodes the object's geometry in a phase profile that can be classified for effectively than in the case of the other three policies, which attempt to encode information in the waves's power. Notably, ObjFocusConf performs better out of these policies, as it increases the amount of power impinging upon the object, and essentially making the encoded information stand out better from the noise.

An interesting prospect is that these two policies could be combined in the future. Moreover, the random phase profile could be adaptive instead of static, e.g., performing a coarse classification first via a completely random-phase wavefront, and then proceeding to adapt in order to discern finer features of the object under study.

V. Conclusion

This work examined four PWE Configuration Policies for object classification using RF-Imaging. Each configuration guides the scattered wavefront to best EM-describe the object at the receiver antenna. The study found that configurations encoding object geometry in random phase shifts of the received wavefront are most beneficial. Additionally, policies focusing more power on the 3D object also enhance classification. Finally, in future work we will explore configurations utilizing complex RIS functionalities, emphasizing phase and power control of the wave.

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