RECONFIGURABLE INTELLIGENT COMPUTATIONAL SURFACES: WHEN WAVE PROPAGATION CONTROL MEETS COMPUTING

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ABSTRACT

The envisioned sixth-generation (6G) of wireless networks will involve an intelligent integration of communications and computing to meet the urgent demands of task-oriented applications. To realize the concept of the smart radio environment, reconfigurable intelligent surfaces (RISs) are becoming promising options for offering programmable propagation of impinging electromagnetic signals via external control. However, the purely reflective nature of conventional RISs induces significant challenges in supporting a variety of computation tasks, such as wave-based calculation and signal processing. To fulfill such computing demands, new metamaterials are needed to complement the existing technologies of reconfigurable surfaces, enabling further diversification of electronics and their applications. In this event, we introduce the concept of reconfigurable intelligent computational surface (RICS), which is composed of two reconfigurable multifunctional layers: the reconfigurable beamforming layer, which is responsible for tunable signal reflection, absorption, and refraction, and the intelligence computation layer, which concentrates on meta-materials-based task-oriented computing. By exploiting the recent trends in computational metamaterials, RICSs have the potential to make joint computation and communication a reality. We further demonstrate two typical tasks of RICSs, in particular a spectrum learning task for intelligent communications and a signal processing task for physical layer security. Future research challenges arising from the design and operation of RICSs are finally highlighted.

INTRODUCTION

As a key enabler for building smart wireless environments, metamaterials, sometimes known as metasurfaces, are engineered materials with promising artificial properties that are not exhibited by natural materials. Recent advances in the design of such materials offer exciting opportunities for unprecedented control and manipulation of electromagnetic (EM) properties, thereby promoting the emergence of reconfigurable/programmable metasurfaces. In such context, reconfigurable intelligent surfaces (RISs) have the potential to significantly improve the quality of communication in the sixth-generation (6G) of wireless networks, by intelligently reconfiguring the wireless propagation of EM signals via low-cost passive reflecting elements (meta-atoms). For example, in communication scenarios with obstacles between the transmitter and receiver, virtual line-of-sight links can be created through RIS's reflections to improve the desired received signal strength and extend the wireless coverage. Additionally, by configuring the reflection coefficients of RIS elements appropriately, the co-channel/inter-cell interference can be suppressed, EM field exposure can be tamed, and physical-layer security can be further improved.

Although RISs constitute an emerging technology for creating an intelligent wireless radio environment, they are not capable of performing tasks other than wireless communications via passive reflection, thereby not satisfying the quality-of-experience (QoE) demands of envisioned future advanced tasks that involve both communications and computing. In contrast to existing efforts on RISs, in this article, we elaborate on a significant question: *"why and how can task-oriented wireless communication and computation be achieved for future intelligent networks?"* To answer this question, we introduce a motivating example to illustrate the inevitability of the task-oriented metamaterials and demonstrate the indispensability of the proposed reconfigurable metasurfaces.

In the conventional RISs-empowered wireless communication systems, the interfering signals tend to dynamically fluctuate and the conventional RIS "blindly" reflects both the desired and interfering signals. Due to the unpredictable nature of interfering signals, undesired reflections via RISs become a critical challenge, which is known to severely degrade the desired signal at the receiver [1]. To solve this challenge, carrying out the
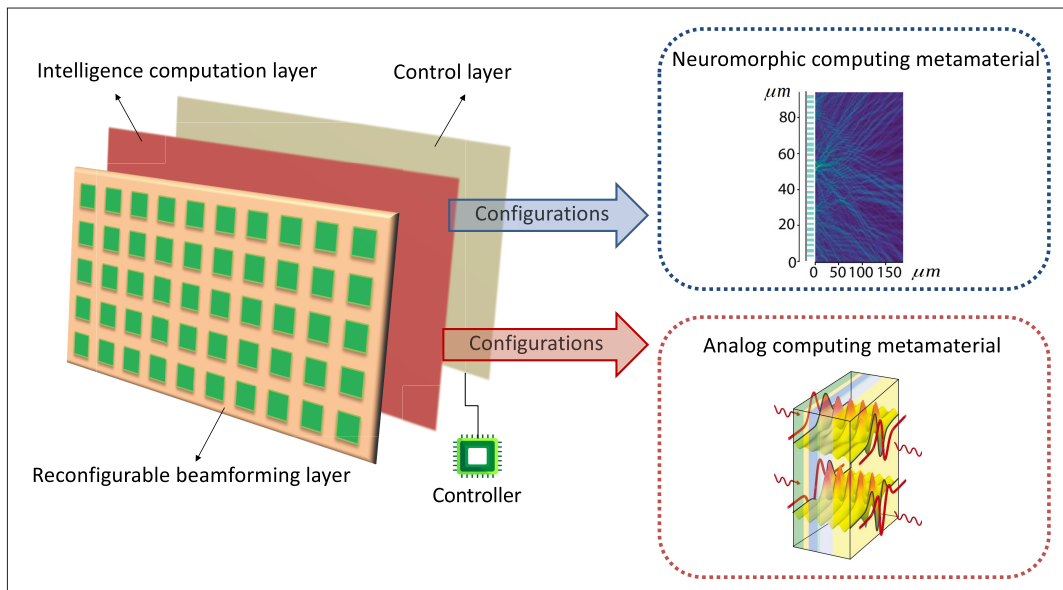
FIGURE 1. The architecture design of an RICS. It contains three layers: a reconfigurable beamforming layer, an intelligence computation layer, and a control layer. In order to meet the diversification of computational tasks, the intelligence computation layer can be configured by different kind of metamaterials, for example, neuromorphic computing metamaterials for wireless spectrum learning (shown on the top-right [4]) or analog computing metamaterials for secrecy signal processing (shown on the bottom-right [5]).

tasks that involved both communication and computation via RISs becomes necessary. If the conventional RISs are empowered with some basic computational capabilities to perform active EM sensing for interference estimation, such a technical challenge could be mitigated with very low extra hardware cost [2]. Specifically, by exploiting the intrinsic potential of metamaterial-based computing techniques, certain task-specific computing operations, such as mathematical functions (e.g., spatial differentiation, integration, and convolution) and artificial neural inference, can be achieved [3]. This kind of structure is referred to as *computational metamaterials*, which specializes in task-oriented computation on processing wireless signals, images through neuromorphic computing, and/or optical analog computing [4, 5].

At the task-execution level, computation efficiency plays an important role for improving the QoE of the tasks. Compared to traditional task-independent computing, a potential trend of future metamaterials is the task-oriented driven design, where the task is computed according to its specific features. That is to say, the computation tasks are performed based on the prior knowledge, which can be achieved via an artificial neural network [6]. For instance, a programmable artificial intelligence machine structure has been recently proposed to handle various deep learning tasks via manipulating the reflected or transmitted EM waves [7]. In this context, the task-oriented driven metamaterials design has potential to provide the unique possibility of extraction of task-relevant information, thereby enhancing the tasks' computation efficiency substantially.

Inspired by the above, *it is foreseen that future intelligent metasurfaces will integrate task-oriented computation with communications functions via computational metamaterials.* In this article, we explore a new structure of intelligent metasurfaces that exploits the natural superiority of computation-

al metamaterials to simultaneous enable dynamically adjustable signal reflections and task-oriented computation. In particular, we term these structures "reconfigurable intelligent computational surfaces," and abbreviate them as "RICSs."

FUNDAMENTALS OF RICS

Compared to materials found in nature, the properties of metamaterials, such as permittivity and permeability, stem from the form of their atomic design. Recently, the interest in analog computing was revived in the context of metamaterials [8]. In this context, the proposed RICS belongs to a composite material, which is designed and optimized to function as a means to control the EM waves as well as to perform computation tasks. Different from conventional RISs that can only reflect their incoming signals, the proposed RICS structure is composed of three layers: the *reconfigurable beamforming layer*, the *intelligence computation layer*, and the *control layer*, as conceptually sketched in Fig. 1. The first two multifunctional layers interplay with each other and should be jointly configured. The inner control layer is a control circuit board that implements a smart controller, which focuses on adjusting the tunable parameters of the beamforming layer and can be implemented via field-programmable gate arrays.

In the following, we introduce the design of the first two layers: the reconfigurable beamforming layer and the reconfigurable computation layer. Then we demonstrate the architectural design of the RICS, which can be used to reflect signals as well as perform computational operations.

RECONFIGURABLE BEAMFORMING LAYER

The reconfigurable beamforming layer commonly comprises a number of tunable elements, which can be dynamically configured to intelligently *reflect*, *refract*, or *absorb* the incident radio frequency (RF) signal. In particular, due to the specific demand of

Determined by the growing demands of computational applications, the intelligence computation layer can consist of different kinds of computational metamaterials, such as neuromorphic computing metamaterials and analog computing metamaterials for performing certain specific task in near-real-time.

computation tasks, these tunable elements can be designed to have four kinds of operations.

Reflection: This operation indicates that the elements act just like the conventional passive elements that reflect the incident RF signal.

Refraction: In this operation, the incident RF signal can be simultaneously reflected and refracted toward both sides of the reconfigurable beamforming layer. For instance, by controlling the ON-OFF state of the positive-intrinsic-negative (PIN) diode of each element [9].

Absorption: By enabling this operation, some portion of the tunable elements work as receivers with reception RF chains, thereby allowing to further process the received signal in the digital domain.

Storage and Retrieval: This operation enables the storage and retrieval of the EM waves by exploiting the electromagnetically induced transparency effect.

Based on the configured operations of the tunable elements, the operating mode of the reconfigurable beamforming layer can be categorized into two modes.

Reflection-Absorption (RA) Mode: This mode mainly consists of two types of elements: the conventional passive reflecting elements and *semi-active elements* for incident RF signal processing. Specifically, for the semi-active RICS elements, only few RF front-ends, analog-digital conversion, and down-conversion are required, to enable information sensing from the incident wireless signals, for example, achieving the Inphase-and-Quadrature (I/Q) sequences. Hence, baseband processing for signal decoding is unnecessary, avoiding the deterioration of tunable reflections since only very few semi-active elements are needed. Different from the active elements requiring full RF chains for sensing, our proposed semi-active elements results in less hardware requirements.

Reflection-Refraction (RR) Mode: To simultaneously realize reflection and refraction, the incident energy is split into two parts: some of the energy is reflected while the remaining of the energy is refracted to serve users located on the opposite side.

INTELLIGENCE COMPUTATION LAYER

Determined by the growing demands of computational applications, the intelligence computation layer can consist of different kinds of computational metamaterials, such as neuromorphic computing metamaterials and analog computing metamaterials for performing certain specific task in near-real-time.

Neuromorphic Computing Metamaterials: To realize artificial neural computing with faster speed and lower energy consumption, optical neuromorphic computing was proposed, especially for achieving multi-class classification, by leveraging optical reflection through neuromorphic metamaterials, as shown in top-right of Fig. 1. For instance, the neuromorphic computing metamaterial based intelligence computation layer can consist of an array of TiO2 pillars on top of a SiO_2 substrate [10].

Principle: Emerging neuromorphic metamaterials generally consist of multiple layers of nanostructures, which are composed of an array of nanoribbons. By changing the size of the ribbons, the amplitude and phase of scattered light can be controlled. Similar to the training of traditional deep neural networks, training the neuromorphic

metasurface can be a gradient descent process that aims at minimizing the loss function. The difference is that the additional trainable parameters of neuromorphic metasurface include the widths of the nanoribbons. After going through a few layers of the appropriately trained neuromorphic metasurface, the output light becomes a focused beam, which points toward a spatial location corresponding to the inferred class.

Operating Mode: The operating mode of the intelligence computation layer via neuromorphic computing metamaterials is denoted as the neuromorphic-computing (NC) mode. For the NC mode, the intelligence computation layer consists of multiple tiers of nanostructures, which are composed of an array of nanoribbons on top of a dielectric substrate. The well-trained intelligence computation layer particularly serves the purpose of classification problem via neuromorphic computing. For instance, when a plane wave illuminates an object and passes through the intelligence computation layer, this layer then scatters the light in a way that is equivalent to artificial neural computing. In general, the input of neuromorphic computing metamaterials is the light scattered by an object, which is usually resized and converted into a digital vector first.

Analog Computing Metamaterials: In recent years, the study of analog computing through metamaterials has attracted wide attention due to the advantages of parallel processing with ultra-high speed. Different from the fresh literature of intelligent surfaces design that conventionally uses digital units (such as received RF chains and computational/storage units [11]) to achieve signal processing, the intelligence computation layer with analog computing metamaterials is able to perform computation tasks more efficiently (i.e., processing latency is very low), as highlighted in the bottom-right of Fig. 1. To replace circuits with computing metamaterials, two approaches can be implemented by letting EM waves propagate through metamaterials, such as the Green's function approach and the metasurface approach [8].

Principle: Owning to the powerful wave manipulation abilities and subwavelength characteristics, the EM metamaterial can perform mathematical operations, such as spatial integration, differentiation, and convolution. There exist two popular approaches to achieve this functionality: the metasurface approach, and the Green's function (GF) approach, by which the computation can be directly performed on an analog signal. Specifically, the metasurface approach performs signal processing in the Fourier domain based on suitably designed metamaterial blocks that can perform mathematical operations. Each metasurface block is composed of a layered structure of two alternating materials, for example, Aluminum-doped zinc oxide and silicon. The metasurface approach consists of three sub-blocks: two Fourier transformers via graded-index and lenses, and an optical metasurface between the two graded-indexes for realizing the mathematical operation of choice. By suitably manipulating the impinging wave to propagate through the metamaterial blocks, signal processing can be achieved accordingly. In the GF approach, the multi-layer structure is composed of a stack of subwavelength metamaterial (e.g., dielectric)

	Architecture design	Key features	Limitations and challenges
Conventional RIS	Consists of one reflection layer with almost passive elements, which are adjusted by a dedicated controller	Superposed multi-path signals impinge on each element, which provides tunable reflection, enhancing signal strength at a remote receiver	Purely passive reflective nature
Hybrid RIS [8]	Consists of one reflection layer with hybrid elements, which can be used for simultaneous reflection and sensing of the incoming signal	Each or groups of elements are attached to a waveguide, each connected to a reception RF chain, thereby enabling to sense a portion of the impinging signal via analog combining, and then, locally process it in the digital domain via a relevant unit	Additional power and complexity are introduced for signals sensing and local processing of the sensed information
Proposed RICS	Consists of the reconfigurable beamforming layer and the intelligence computation layer, thereby enabling wireless communications and computation via metamaterials	Computational metamaterials are used for performing certain computing tasks, without the requirement of analog combining circuitry, digital processing unit, and relevant converters, thereby involving lower power consumption and hardware complexity	Relies on computational metamaterials and on their joint design with the reconfigurable beamforming layer

TABLE 1. Comparison of the proposed RICS stricture with purely reflective and passive RISs as well as hybrid RISs.

slabs. By optimizing the permittivity, permeability, and thickness of each slab, it is feasible to carry out the computation directly in a spatial domain without involving additional Fourier lenses.

Operating Mode: The working mode of the intelligence computation layer via analog computing metamaterials is denoted as the analog-computing (AC) mode. The AC mode particularly serves the purpose of signal processing via mathematical-based analog computing. In particular, the intelligence computation layer that works in this mode consists of multi-tiered dielectric slabs, thereby allowing the synthesis of mathematical operations of interest. By optimizing the permittivity, permeability, and thickness of each slab, the intelligence computation layer can act as certain mathematical operations on the incident refracted signal to match the considered transfer function without involving additional Fourier lenses.

In contrast to conventional solely reflective RISs and hybrid RISs for simultaneous tunable reflections and signal sensing [8], computational metamaterials can be designed for both signal reflection and specific computation tasks, without the requirement of additional computational units and analog combining circuitry, thereby involving lower power consumption and reduced hardware complexity, as highlighted in Table 1.

RICS Architecture Design

Based on the configurations of the reconfigurable beamforming layer and the intelligence computation layer, we present two kinds of RICS designs:

RICS-Design-A — RA+NC: This design is achieved via neuromorphic computing metamaterials, as shown in Fig. 2. Taking the task of wireless spectrum sensing as an example, to explore the potential of NC mode, data visualization needs to be utilized to map the wireless spectrum data into a unique image, which is, in turn, suitable for the neuromorphic computing metamaterials. Specifically, when the incident RF signal arrives at the reconfigurable beamforming layer working at the RA mode, the impinging signal is received via the semi-active absorption elements, while the remaining reflection elements reflect the signal in a conventional passive way. The received signal is transferred to an I/Q vector, which is then mapped into an image and further fed into the
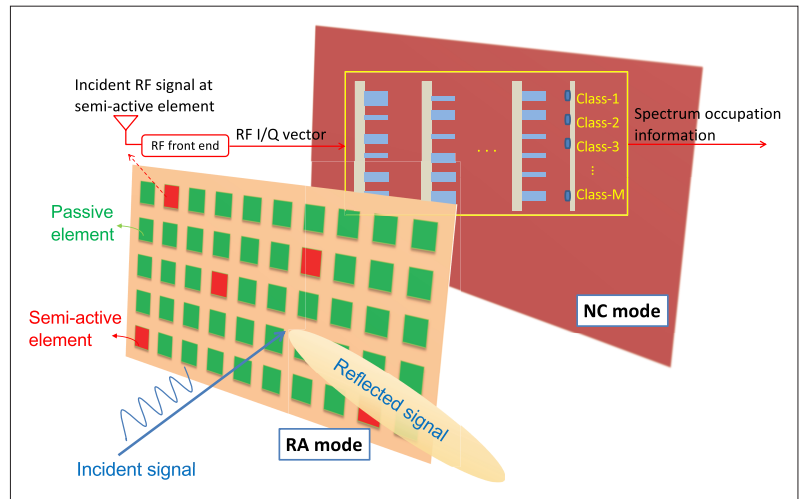

FIGURE 2. The RICS-Design-A with RA+NC mode.

intelligence computation layer working as the NC mode. The final output indicates the class inferring the components of the incident RF signal.

RICS-Design-B — RR+AC: This design is achieved via analog computing metamaterials, as shown in Fig. 3. Different from the RICS-Design-A, when the incident RF signal arrives at the reconfigurable beamforming layer, the incident energy is divided into two parts: The reconfigurable beamforming layer is configured as the RR mode since the input of the intelligence computation layer is the original analog signal. In particular, some energy is used to reflect the impinging signal while the rest of the energy is for refracting the signal. Then the refracted signal is considered as the input to the intelligence computation layer with the AC mode. By performing analog computing, the output of the intelligence computation layer demonstrates the specific mathematical operation of the incident signal.

Nowadays, intelligent reflection communication empowered wireless spectrum sensing and physical security are regarded as key features of supporting advanced tasks from society and industries [12]. To demonstrate the potential of RICSs, in the following sections, we present two illustrative computational tasks of RICSs: intelligent spectrum sensing and secure wireless communications.
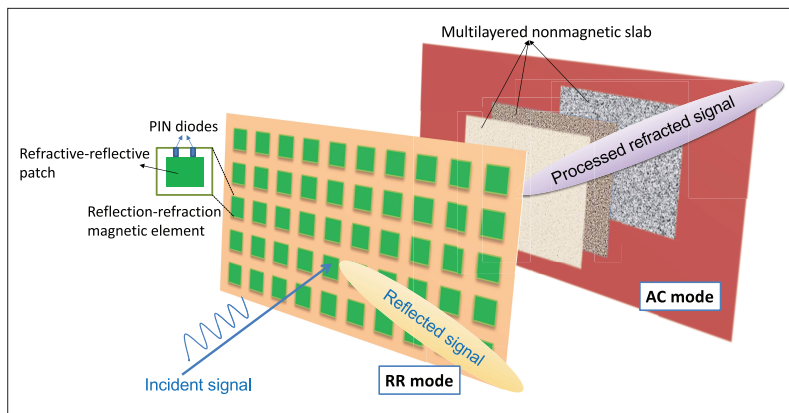
FIGURE 3. The RICS-Design-B with RR+AC mode.

SPECTRUM LEARNING VIA RICS-DESIGN-A

In this section, we present an RICS-Design-A application, which takes advantage of the neuromorphic computing metamaterials to perform the task of intelligent spectrum sensing while communicating.

MOTIVATION

In the context of tasks-oriented communications in future 6G wireless networks, integration of wireless sensing and communications has become an inevitable trend. Currently, RISs have been commonly used to improve the quality of wireless links by appropriately reflecting the incident signals. However, due to the unpredictable superposition of the wireless signals, undesired reflections of both the desired and interfering signals become a critical challenge, which may cause a deleterious effect on the receiver via the conventional RISs.

To address this challenge, it turns out that exploring wireless environments via RF spectrum learning becomes beneficial, which, however, requires a large amount of computing resources and power. This motivates the necessity to perform the task of wireless spectrum learning via the proposed RICS, thereby enhancing the performance of wireless communications.

PROCEDURE

Due to the uniqueness of the wireless signal, the wireless spectrum learning task can be considered as a classification problem and then addressed via a trained deep neural network model. With the inferred spectrum information given by RICS, the base station (BS) can improve the spectrum efficiency via allocating the wireless resources intelligently for future 6G networks.

An illuminative example is illustrated in Fig. 4a, where three users (e.g., U_1, U_2, and U_3) communicate with a BS via the RICS. The BS maintains a control link with a controller of the RICS, where the RICS sets the configuration as the RICS-Design-A. Under such setups, an eight class classification problem is described as follows:

- Class 1 - "Idle": noise only.
- Class 2 - "U_1": user U_1 only.
- Class 3 - "U_2": user U_2 only.
- Class 4 - "U_3": user U_3 only.
- Class 5 - "$U_1 + U_2$": users U_1 and U_2.
- Class 6 - "$U_1 + U_3$": users U_1 and U_3.
- Class 7 - "$U_2 + U_3$": users U_2 and U_3.
- Class 8 - "$U_1 + U_2 + U_3$": users U_1, U_2, and U_3.

To realize spectrum learning via RICS-Design-A, we first train an optical neural network (ONN) model in the intelligence computation layer. Specifically, we collect RF traces by building a universal software radio peripheral based testbed and store the RF traces as I/Q sequences. With the collected I/Q data with different signal combinations, the ONN model is trained offline via stochastic gradient descent method, which is further performed repeatedly until the loss function converges.

After the ONN model is appropriately trained, wireless spectrum sensing can be achieved via online inference at the RICS. Specifically, once the incident RF signals arrive at the reflection-absorption layer, a portion of elements reflect the signal in a conventional way while the remaining elements vectorize and process the signal. Note that before feeding the I/Q vector to the trained intelligent computation layer, data preprocessing, such as frequency adapting and data visualization, is required. Then the spectrum information can be output by performing forward calculation via ONN inference. Consider that conventional RISs whose working bandwidth may be very limited due to their inherent implementation restricts, the RF signals impinging at the RICS are encouraged to be mixed through the same frequency bandwidth, so as to obtain the I/Q samples at the RF chain for further spectrum sensing.

ILLUSTRATIVE RESULTS

The considered application scenario for evaluating the RICS-Design-A is shown in Fig. 4a, where three users ocassionally send data to the BS using the transmit power 200 mW and the data payload size of each user is 1000 bits. The distance between the users and the RICS is 60 m, the distance between the RICS and the BS is 80 m, the incident angle between the users and the BS is 160°. Moreover, the noise power density is –174 dBm/Hz, the wireless bandwidth is 10 MHz, and the power ratio of the reflected and refracted signals is 1.

We focus on a wireless spectrum sensing task using the trained ONN model for classification [13]. Specifically, we trained a 2 and 4 layer model with the collected RF dataset, consisting of a total of 100 million I/Q samples indicating one of the eight classes. Upon convergence, the 2 layer model achieved 85 percent accuracy for spectrum sensing, wheres the 4 layer model resulting in 90 percent accuracy. This demonstrates that the inference accuracy can be improved when more layers are used. However, the number of layers needs to be chosen carefully to achieve the desired trade-off between inference accuracy and complexity.

To evaluate throughput performance, we further implement a time division multiple access scheme for RICS and RIS, respectively. Then we evaluate and compare the achieved network throughput, as illustrated in Fig. 4b. Different from statistical time slots allocation with the conventional RIS, we observe that the RICS transmission schemes are always superior to the conventional RIS-based scheme since the RICS can infer the incident signal components, thereby enabling the BS to allocate time slots for the active users intelligently. Reflected in Fig. 4b, we also note that the inference accuracy achieved by the trained ONN model at the RICS affects
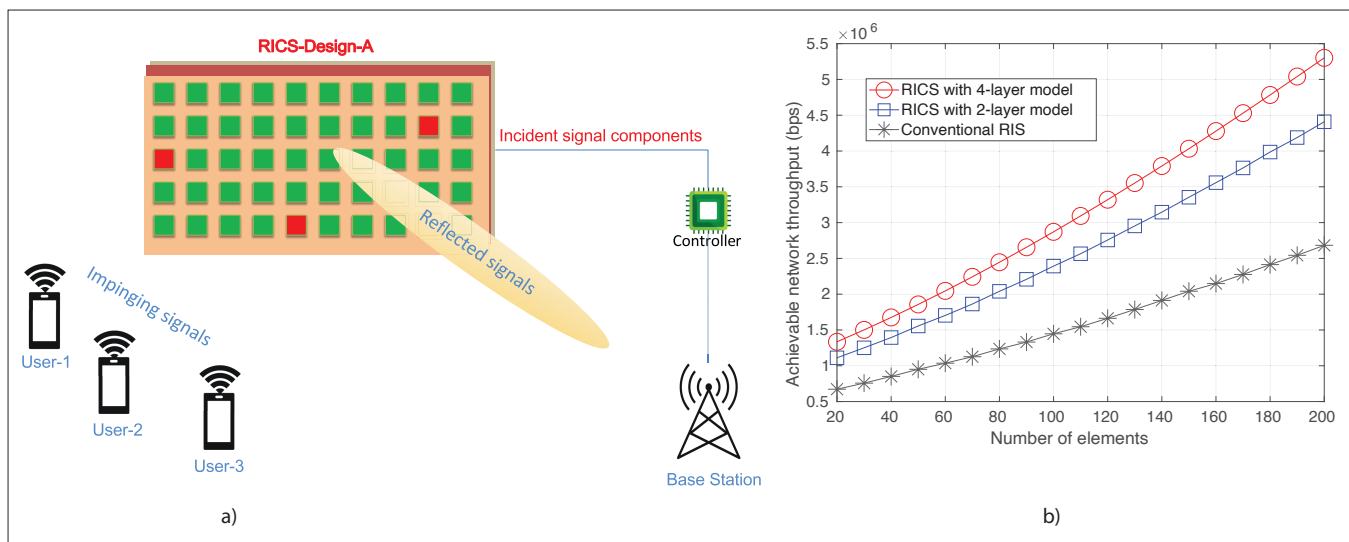
FIGURE 4. An illuminative example of RICS-aided intelligent spectrum sensing, where three users transmit to a base station via the RICS-Design-A. Specifically, the application scenario is illustrated in a), and the achieved network throughput versus the number of elements is shown in b).

the network throughput significantly. In particular, compared to the RICS with 2-layer model, the RICS with 4-layer model outperforms and the performance gap becomes larger as the number of elements increases.

Physical Layer Security via RICS-Design-B

In this section, we present an RICS-Design-B application, which takes advantage of the analog computing metamaterials to perform the task of secure wireless communications.

Motivation

In recent years, physical layer security has attracted increasing attention from research and industrial communities. Suppose an eavesdropper in the network, when the user transmits data to a legitimate receiver, information leakage may occur since the eavesdropper may intercept this wireless communication.

To address this challenge, deploying a conventional RIS for generating dynamically safeguarding reflected signals has become a recognized solution. In particular, the signal reflected by an RIS can be tuned out to cancel the signal received at the eavesdropper, which is usually assumed to lie on the same-side with the legitimate user. However, the unavailability of computational capability at the RIS and the lack of prior information about the eavesdropper constitute a stumbling block for reducing information leakage in practice, especially when the eavesdropper is located on the *opposite-side* of the RIS. These motivate the desirability of performing incident signal processing, thereby suppressing the received signal-to-interference-plus-noise (SINR) at the eavesdropper.

Procedure

With the implementation of an RICS, the incident signal can be refracted at the reconfigurable beamforming layer and adjusted appropriately by the intelligence computation layer. Then the processed signal can be destructively added with the non-reflected signal at the eavesdropper to neutralize the leaked signal.

An illustrative example is shown in Fig. 5a, where a sender transmits data to a receiver and an eavesdropper is nearby. We note that the wireless signal that comes from the sender can also be received at the eavesdropper. Different from the conventional RIS without computing capability, the RICS-Design-B can be exploited to generate an intended interfering signal to worsen the quality of the leakage of the signal.

Specifically, when the incident signal arrives at the reconfigurable beamforming layer of the RICS, the energy of the incident signal is divided into two parts: Some of the incident energy is reflected to serve the desired receiver located on the same side as the sender, and the rest of the energy works for impinging signal refraction. Since the channel model of the reflected and refracted signals may not be symmetric, the power ratio of the reflected and refracted signals in the reconfigurable beamforming layer could be appropriately optimized [9], thereby providing an extra degree of freedom for enhancing the RICS-aided communication performance. Then, by feeding the refracted signal to the intelligence computation layer that works in the AC mode, an intended interfering signal can be appropriately generated by performing the mathematical operation to the incident signal, for example, frequency shifting, to further worsen the leaked signal at the eavesdroppers who located at the opposite side of RICS. Instead of relying on higher-layer encryption, the RICS enables the exchange of confidential messages over a wireless medium in the presence of unauthorized eavesdroppers.

Illustrative Results

The considered application scenario for evaluating the RICS-Design-B is shown in Fig. 5a, where the distance between the RICS and the eavesdropper is 50 m and other critical parameters are kept unchanged. The power ratio between the reflected signal and the incident signal is denoted as α, the power ratio of between the refracted signal and the incident signal is denoted as β, and $\alpha + \beta = 1$ holds in the simulations.
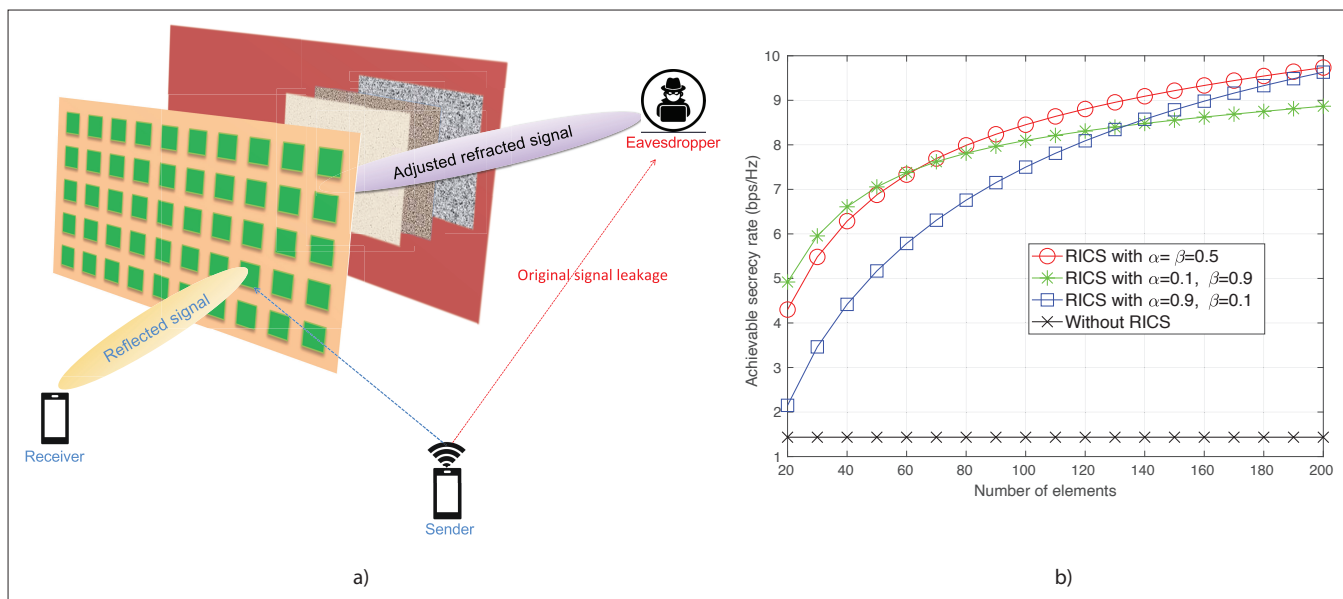
FIGURE 5. An illuminative example of RICS-aided secure wireless communication, where an intended interfering signal is generated via the RICS-Design-B to worsen the quality of the signal at the eavesdroppers. Specifically, the application scenario is illustrated in a), and the achieved secrecy rate versus the number of elements is shown in b).

To demonstrate the performance of secure wireless communication via the RICS-Design-B, we evaluate the achievable secrecy rate in b/second/Hertz (bps/Hz), which can be expressed as the achievable secrecy rate, and is the difference between the achievable rate of the legitimate link and the eavesdropper link.

Figure 5b compares the achievable secrecy rates of four schemes. We observe that the achievable secrecy rate of the three schemes that are based on the RICS is higher than that of the scheme "Without RICS," and the performance gap increases as the number of RIS elements grows. This indicates that with more reflecting elements, the reflect and refract beamforming design of the RICS becomes more effective, thereby achieving higher gains of secrecy rate. We also observe that the power ratio coefficients, α and β, play a significant impact on the achievable secrecy rate performance. In particular, when the number of elements is small, for example, less than 60, a lower value of α brings a beneficial impact on the RICS. As the number of RIS elements increases, the scheme with a larger value of α outperforms. It is worth mentioning that there exists an optimal trade-off between the reflected power and the refracted power for a given number of elements of the RICS.

CONCLUSION AND FUTURE DIRECTIONS

In contrast to purely reflective RISs, RICSs offer the capability of performing certain tasks via computational metamaterials, enabling both communications and computation applications. In this article, we discussed two motivating examples, although many others need to identified, which contribute toward the direction of RICSs embedded with task-oriented computational metamaterials and relevant operation protocols.

NONLINEAR COMPUTING METAMATERIALS

Note that the analog computational metamaterials discussed in the proposed RICS structure are usually related to linear functionalities. With the emerging demands of complex computing tasks, investigating the possibility of performing nonlinear processing operations through computational metamaterials is necessary. In this event, nonlinear signal processing technologies has become a potential player for improving the performance of future 6G wireless system.

To swim with the tide, the concept of metasurfaces is undergoing transformation for the realization of nonlinear functionalities [8]. In such a context, investigating the possibility of performing more complex calculations and operations via RICSs with nonlinear-enabled computational metamaterials becomes an attractive research direction.

MULTIFUNCTIONAL COMPUTING METAMATERIALS

At the metamaterials level, enhancing the speed of computation is important for the implementation of RICSs. Compared to the single-task processing for analog computing design, an important trend in computational metamaterials is multifunctional based analog computing, in which multiple computational tasks can be performed simultaneously via different independent processing channels. As a result, such multifunctional computing metamaterials can provide the unique possibility of parallel processing of information and, thus, enhance the computation performance.

Under this trend, the development of task-oriented multifunctional computational metamaterials will open a new route for the intelligent metasurfaces design with accelerated processing capability based on the prior knowledge of different specific tasks.

ARTIFICIAL INTELLIGENCE EMPOWERED DESIGN

The RICS configurable profile, such as phase shift matrices in the reconfigurable beamforming layer and the parameters settings of the intelligence computation layer, has to be optimized for enhancing the network performance. In practical deployments, each RICS could be equipped with

hundreds of meta-atoms. However, most of the existing contributions tend to rely on mathematical model-based optimization methods, which generally require a large number of iterations to find a near-optimal solution due to the non-convex natures of the constraints and the objective function.

With the development of advanced AI tools, investigating the possibility of metasurfaces design using deep neural networks, or other machine learning structures, is of interest. In contrast to the conventional optimization methods for non-convex equation solving, deep learning can help to quickly infer the optimal solutions for the configurations of metasurfaces with higher accuracy [14]. In the future, due to privacy concerns and scarce wireless computation resources in practical scenarios, introducing advanced edge learning techniques to enable the realization of the proposed intelligent RICS design seems appealing [15].

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In practical deployments, each RICS could be equipped with hundreds of meta-atoms. However, most of the existing contributions tend to rely on mathematical model-based optimization methods, which generally require a large number of iterations to find a near-optimal solution due to the non-convex natures of the constraints and the objective function.

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