A survey of Intelligent learning techniques in Reflecting Intelligent Surfaces

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Abstract

With the development of IoT in recent years, the focus of future communication systems has shifted to machine-to-machine (M2M) communications. This is in stark contrast to the focus on human-to-human (H2H) communications up to 4G communication systems. 5G has diversified its approach to the problem of effective communication by incorporating many different verticals representing different classes of communications. However, the rapid growth of IoT has proven to be overwhelming for the strategies currently envisioned to enable communication. One of the key enabling technologies anticipated to support the demands of future wireless communication systems is reflecting intelligent surfaces (RIS). Both ideal and practical models have been used to construct simulation environments, which have also paved the way for the use of data-driven approaches such as machine learning and deep reinforcement learning (DRL). In this article, we provide an overview of the intelligent data-driven solutions that have been explored for the optimization of RIS-enabled systems and attempt to construct a classification for better exploration of the existing literature on the subject.

Ⅰ. Introduction

The development of IoT in recent years and its rapid adoption due to its automation potential has focused attention on the need to support machine-to-machine (M2M) communications. The global IoT market is expected to grow to 1386.06 billion by 2026, and the amount of data transmitted by IoT devices is expected to reach 73.1 ZB[1]. The diversification of connected device requirements has been anticipated in the development of 5G infrastructure, and this is reflected in the division of 5G infrastructure into different application classes, which are assumed to have different quality of service (QoS) requirements. In recent years, however, the era of massive IoT has brought demands that are expected to exceed the capabilities of the 5G infrastructure. Augmented reality, autonomous driving, and massively connected devices communicating with each other to provide coherent and seamless experiences are likely to have more stringent service requirements. Therefore, efforts must be made to effectively and efficiently meet the demands of future application scenarios.

To meet the diverse QoS requirements of future application scenarios, new technologies have to be introduced into the current communication ecosystem. These enabling technologies are expected to support the operation of future wireless communication systems by constructing feasible architectures that can meet the stringent requirements of various application classes. One of the key enabling technologies that is expected to play an influential role in the development of future wireless communication systems is reflective intelligent surfaces (RIS). RIS are planar surfaces composed of passive and/or active reconfigurable reflecting and/or transmitting elements that allow controlled reflection and/or transmission of incident electromagnetic (EM) waves. This controlled reflection and/or transmission of the EM waves allows them to effectively reconfigure the channels between the transmitter and receiver.Many different types of RIS have been proposed with different behaviors and operational models. The optimal configuration of the RIS has to be realized based on the channels in order to effectively utilize their reconfiguration capabilities. Many different types of approaches can be employed using modern data-driven techniques to build models that allow the optimal functioning of the RIS and achieve a variety of objectives. In this article, we will provide an overview of the data-driven techniques used in the literature to optimize different objectives under different configurations and types of RIS.

Ⅱ. AI-enabled RIS optimization

Machine learning and reinforcement learning techniques are actively used in many areas of wireless communication research, such as edge learning, channel estimation, beamforming design, and so on. Many of these problems are not convex in practical configurations and require estimation to find a feasible solution in the search space. Advances in data-driven learning techniques have opened new avenues for optimizing complex environments with multiple different entities. In this section, we will provide an overview of the recent literature using these intelligent algorithms in two types of RIS including the normal reflect only RIS and the simultaneously transmitting and reflecting (STAR) RIS.

a. Reflect only RIS

A reflect only RIS is the most basic type of RIS considered in the study of RIS-enabled systems. It serves only to reflect the waves incident on its surface and redirects them towards the desired user in such a way as to constructively interfere with the signal to the user from the direct link, leading to increased signal quality. Many authors have addressed the joint optimization of transmit beamforming vectors and reflection coefficients[2] to maximize the rate[3] or minimize the power consumption[4] using deep learning and DRL algorithms. RIS has also been explored in the context of enabling other communication technologies expected to play a major role in future wireless infrastructure. The flexibility of RIS deployment allows them to be mounted and used alongside any entity and in almost any desired configuration. They can be mounted on high altitude platforms (HAPS)[5], on UAVs[6] and even on aircrafts[7] etc.

Owing to the numerous deployment approaches, many use cases have been explored in the literature, and optimization schemes have been designed with multiple objectives in mind. Deep reinforcement learning has been explored for beamforming design in multi-hop networks, secrecy rate optimization, spectral efficiency maximization, coverage and capacity maximization, etc.

a. STAR-RIS

STAR-RIS, as explained earlier, is a more flexible and generalized implementation of reflect only RIS. It allows the impinging signals to be both transmitted and reflected by the elements present on the RIS. This of arrangement allows to mitigate a noticeable limitation of reflect only RIS and to serve the half planes on both sides of the RIS by allowing the signals to pass through the elements of the STAR-RIS.

Owing to the extended features offered by the RIS, new modes have to be defined that support the use of these features within a deployment. Energy splitting is a configuration in which the energy of the incident signal is split between transmission and reflection. A tunable parameter allows the elements to adjust the amount of energy split between transmission and reflection. Time splitting allows the elements to adjust and transmit all of the incident signals for a fixed amount of time, and reflect all of the incident signal in the next time slot. Mode splitting allows some elements of the RIS to transmit incident signals while enabling other elements to reflect the signals at the same time. These configurations can be used in different deployments to support the operation of communication systems.

STAR RIS has been employed to realize energy-efficient architectures enabled by DRL algorithms. DRL algorithms have also been used for spectrum allocation, configuration design[8], deployment optimization, beamforming design and secure communications etc. of STAR-RIS supported systems. Due to the presence of multiple entities and an uncertain solution for each realization of the system, standard deep learning approaches have been largely unpopular. However, some problems including spectral efficiency maximization and sum-rate maximization etc. have been explored using typical deep learning techniques.

Ⅲ. Conclusion

In this article we provide a brief introduction to RIS and STAR-RIS alongside their operating principles, uses and optimization potential. We briefly outline the works currently present in literature that have made use of deep learning and deep reinforcement learning algorithms for the optimization of RIS and STAR-RIS enabled systems. As more computing resources become widely accessible, the use of these optimization techniques shows significant promise.

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