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RESEARCH ARTICLE

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Embedded Intelligent Reconfigurable Metasurface Architectures for Adaptive Full-Duplex RF Front-End Systems

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Abstract

Radio-frequency (RF) front-end systems that are full-duplex provide the opportunity to ameliorate spectral efficiency, where simultaneous transmission and reception via the same spectral band is possible; these possibilities are harshly restricted due to strong self-interference (SI), dynamic wireless environment, and hardware reconfigurability constraints. This paper suggests an embedded intelligent reconfigurable metasurface architecture to adaptive full-duplex RF front-end systems, in which metasurface control can be modelled by a deep reinforcement learning (DRL)-based control framework. The suggested solution makes metasurface structure and RF cancelation a sequential decision-making task, ensuring the embedded DRL agent will cooperate to optimise SI and signal-to-interference-plus-noise ratio (SINR) with real hardware conditions, such as discrete phase resolution, low update rates, and energy, among others. An architecture based on hardware awareness is designed, combining the configurable metasurface, RF front-end and an inference engine with embedded DRL that is friendly to FPGA/ SoC-dominated devices. The large-scale simulation and hardware-in-the-field testing shows that the proposed DRL-enabled metasurface control performs better in terms of both SI suppression and faster response to channel variations and minimised reconfiguration overhead in comparison with a static and optimization-based and non-learning adaptive baseline control. The findings have been used to emphasise the suitability of learning-controlled reconfigurable metasurfaces as useful and scalable method towards the next generation intelligent full-duplex RF front end system.

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Introduction

Radio-frequency (RF), Full-duplex (FD) Front-end Full-duplex (FD) radio-frequency (RF) front-end systems have become an alternative promising technology in next-generation wireless communication because this concept allows simultaneous transmission and reception in the same frequency band, therefore, potentially doubling spectral efficiency. This paradigm is especially appealing in the case of dense wireless networks, systems beyond 5G/6G and spectrum-constrained systems. Nevertheless, practical implementation of the FD systems is still a problem, mainly because the self-interference (SI) introduced by the transmitter is quite large and may dwarf the intended received signal. The trade-off between SI and low latency and hardware efficiency is an urgent research topic as the wireless systems are now being developed to become intelligent, adaptive and spectrum-efficient architecture.

Dynamic wireless environments, time-varying channels, and non-ideal ties between RF hardware like nonlinearities, phase noise, quantization errors and slow rate of reconfiguration only worsen the severity of SI in FD operation. Traditional SI cancellation methods, across analogies, digital and hybrid space, typically assume a macro level of static or model based conditions that do not generalise in conditions of rapid change. In addition, due to the recurrent reconfigurability of RF components, non-negligible overhead of energy consumption and control is incurred that is especially objectionable in embedded and resource-constrained systems. The necessity of adaptive, intelligent control mechanisms that have the capability to optimise the behaviour of the RF front-end and presence of interference in real-time is driven by these issues.

It is within this framework that reconfigurable intelligent metasurfaces (RIMs) have received a lot of interest as an effective tool of controlling the propagation of electromagnetic waves by software-controlling the phase, amplitude, polarisation, and scattering properties of the surfaces.[1-3] Dynamic control of propagation and coupling of received and sent signal and opportunities to engage programmes in the RF front-end allows adopting opportunities in SI suppression and signal enhancement by influencing propagation and coupling of transmitted and received signals. It has earlier been shown that in smart radio environments, beam forming, and spectrum sharing, metasurfaces and intelligent reflecting surfaces (IRS) have the potential.[5], [7-11] Nonetheless, the majority of the current methods are based on offline optimization, heuristic tuning, or targeted strategies towards static configuration, which do not hold in real-time use of FD over fast changing channel and interference conditions.

To overcome these drawbacks, the current paper will suggest an integrated intelligent reconfigurable metasurface architecture controlled by a deep reinforcement learning (DRL) system to support adaptive multi-way RF front-end systems. The three key contributions of this work are as follows (i) metasurface configuration and RF cancellation formulated as a decision-making problem that can be resolved with the help of DRL, allowing the self-interference to be turned off, and RF front-end performance to be improved, using realistic hardware constraints; (ii) joint optimization problem wherein the same framework can suppress self-interference and harm reduction, as well as optimize the performance of the RF front-end, with realistic hardware constraints; and (iii) the system architecture, in which the reconfigurable metasurface, RF front-end The proposed approach has enabled the intelligence and adaptability of full-duplex RF systems in the next generation possibilities of wireless, through this learning-based and reconfigurable design.

Related Work

Initial studies in full-duplex (FD) RF front-end architectures have been largely concerned with the elimination of self-interference (SI) by using a hybrid scheme of analogue, digital, and hybrid cancellation. In analog, SI is suppressed in advance by low-noise amplification techniques, such as antenna separation, circulators and RF cancellation circuits, whereas in digital, adaptive filtering and signal processing techniques take advantage of the remaining interference, after analog-to-digital conversion, to cancel it. Whereas full SI suppression has been proved under controlled conditions, the techniques usually depend on channel estimates and flawed assumptions about hardware behaviour such that they do not work well under dynamic conditions. In addition, tunable RF front-ends based on tunable philtres, variable attenuators and adaptive matching networks have been investigated in order to enhance flexibility, but are normally controlled heuristically or by rule, so real-time flexibility is restricted, and resistance to reconfiguring them can be high.

In line with the developments in the FD architectures, reconfigurable intelligent metasurfaces (RIMs) have also emerged as a ground-breaking technology to control the propagation of electromagnetic waves in wireless networks. Early research has determined the physical principles, design processes, and applicability of metasurfaces to a wide band of microwave frequencies to optical frequencies.[1, 2] Later literatures proposed the idea of the software controllable and programmable metasurfaces with which characteristics of scattering, reflection, polarisation and focusing could be dynamically controlled.[5, 12] Metasurfaces and intelligent reflecting surfaces (IRS) have been vociferously examined in wireless communications focusing on beam shaping, spectrum sharing, and intelligent radio worlds, and reported significant coverage and spectral efficiency gains,[3], [7-11] Through these studies, it is established that metasurfaces can be a strong reconfigurable element in the RF front-end.

In spite of these developments, the vast majority of metasurface-based wireless systems do sdepend on open-loop operation or offline optimization-based control, with metasurface states being calculated with either deterministic models or iterative solvers. Those methods tend to use quasi-static channels, perfect channel state knowledge and insignificant reconfiguration cost which are not true in real-world full-duplex RF front-end systems. Besides, optimization-based techniques are computationally intractable when (i) the size of the metasurface becomes larger, or (ii) discrete phase and hardware constraints are exerted. An overview of the existing works indicated that the majority of studies that are related to the field are interested in communication-level performance enhancements and do not consider the embedded control viability, real-time adaptation

Table 1: Comparative Literature Review of Metasurface-Enabled Wireless Systems

Reference	Metasurface / RIS Focus	Learning-Based Control	Full-Duplex / SI Awareness	Embedded / Real-Time Feasibility
Glybovski *et al.* [1]	Fundamental metasurface theory and EM modeling	No	No	No
Liaskos *et al.* [5]	Software-controlled programmable metasurfaces	No	No	Limited
Wu & Zhang [10]	IRS-aided wireless communication optimization	No	No	No
Renzo *et al.* [8]	Smart radio environments with AI metasurfaces	Conceptual	No	No
This Work	Reconfigurable metasurface RF front-end integration	**DRL-based adaptive control**	**Yes**	**Yes (Embedded-aware)**

and close integration with the full-duplex RF hardware (summarised in (Table 1).

Learning-based RF adaptation, especially reinforcement learning (RL) and deep reinforcement learning (DRL), has been an increasingly popular subject of interest more recently as a way of enabling model-free and adaptive control in complex wireless systems. DRL has been used in beam forming, spectrum access and interference management and demonstrated more flexibility than classical optimization. Nevertheless, the majority of learning-based methods focus on the optimization of the baseband or network-layer and come with the assumption of a centralised computation and duly equipped resources. DRA metasurface control is not well applied, and all the current literature seldom considers full-duplex operation, self-interference rejection, or hardware restrictions. This means that the embedded DRL frameworks to share the reconfigurable metasurfaces and full-duplex RF front-ends are clearly underdeveloped, which explains why the proposed architecture and learning-based control mechanism developed in this work is inspired.

System Architecture and Problem Formulation

The reference system is full-duplex (FD) RF front-end system that allows transmitting and receiving at the same frequency band to be performed and is depicted in (Figure 1). The transmit (TX) and receive (RX) chains are very close to each other in this architecture, and cause significant electromagnetic coupling and overwhelming self-interference (SI) at the receiver. The signal that is received is then composed of the desired signal of interest, residual SI, and noise. The FD configuration, whereas remote receiver is not grouped in time, as it is in a half-duplex system, requires real-time and sustained mitigation of SI to avoid de-sensitization of a remote receiver and degradation of its performance. That puts SI suppression as a design point in the RF and system-control design between the RF and system controls.

The self-interference channel of the proposed model is noted as a complex interference of direct leakage, multiple path reflections and nonlinear distortions induced by hardware. The SI channel is temporally varying because of the environmental variations and reconfiguration of the RF front-end. Practical hardware constraints are also important factors in system behaviour on top of channel dynamics. These are finite phase resolution of reconfigurable elements, non-negligible switching latency during reconfiguration and power consumption constraints due to embedded platforms. These restrictions cause reconfiguration actions to be performed with more frequency and granularity and they need to be carefully factored in the system model to be real-time feasible.

In order to increase front adaptability during RF fronts, reconfigurable intelligent metasurface (RIM) is incorporated into the system as illustrated in (Figure 1). The metasurface is an array of an array of programmable unit cells, which have the capability of varying the electromagnetic response of the medium by discrete phase and/or amplitude states. These unit cells are automated through an internal interface that is linked to a domestic controller, which allows the manipulation of the wave propagation properties on a software basis. The positioning of the metasurface ensures that it can affect the transmitted and the leaked signals, which in turn enables it to design the SI channel and enhance the isolation of the TX and RX paths. Metasurface reconfiguration however, involves timing overhead and energy usage especially when there is a high rate of change in the environment and the required reconfiguration.

Formulated on the above architecture, the control problem is seen as a multi-objective optimization problem. The main requirements include the reduction of residual self-interference, the maximum signal-interference-plus-noise ratio (SINR) to the receiver, and the minimization of energy and reconfiguration rate used to modify the embedded systems to maintain the efficiency of the embedded system. These goals are practical that is, discrete metasurface state spaces, control bandwidth, and a constraint on integrated hardware resources. The ensuing issue is very nonlinear, time-dependent and challenging to handle with traditional optimisation procedures. This stimulates the implementation of a learning-based and model-free control model, where both the metasurface and RF front-end are adaptively programmed by deep reinforcement learning to give optimization of real time and hardware conscious control.

DRL-Based Adaptive Metasurface Control Framework

In order to be able to real time and model-free adjust the reconfigurable metasurface in a full-duplex RF front-end, the control problem will be formulated in a deep reinforcement learning (DRL) framework as depicted in (Figure 2). Under this formulation, the agent is the embedded metasurface controller, which continuously interacts with environment which is the entire duo of the full-duplex RF front-end, the wireless propagation channel and the self-interference dynamics. During every single decision epoch, the agent can view the system state, choose a control action and get a scalar reward based on RF performance and cost of hardware. The controller can also be able to learn the best policies of metasurface and RF cancellation without the explicit analytical models of the SI channel or RF impairments.

The state space is crafted to record the much-needed information to achieve successful adaptation without compromising with embedded resources constraints. In particular, the state has measurements of residual self-interference power, coarse or estimated channel state information and a succinct description of the metasurface history configuration in order to capture both time correlation and reconfiguration time. The action space will include the metasurface element phase and / or amplitude tuning command, optional RF or digital self-interference cancellation parameter update command. The assemblage of the form of action facilitates combined control of the electromagnetic setting as well as the RF front-end wherein the learning agent can control both the propagation and cancelation mechanisms in an interlink.

The reward function is very critical towards steering the learning process towards hardware-knowledgeable and performance-optimal behaviour. The proposed framework builds a reward, which is a weighted average of self-interference suppression gain, signal-to-interference-plus-noise ratio (SINR) enhancement and penalty conditions related to reconfiguration energy consumption and excessive update rates. The reward aspect of the embedded system objectively deters such behaviours of reconfiguration as frequent reconfigurations and expensive reconfigurations by penalising these behaviours, thus encouraging the efficient utilisation of embedded system resources and achieves consistent control policies. This structure guarantees the balanced performance of the policy learned to practical implementation limitation as illustrated in the feedback loop of (Figure 2).

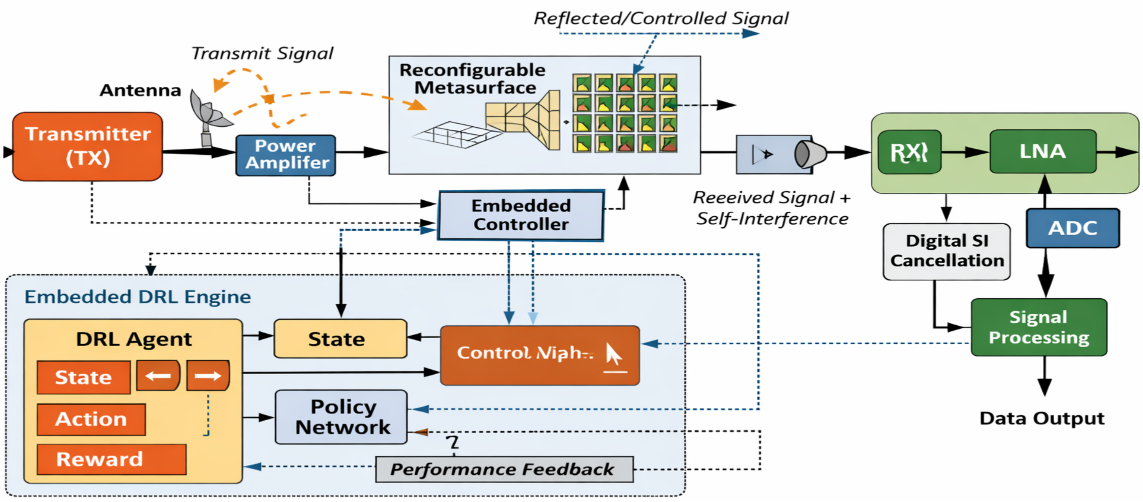

Fig. 1: Embedded intelligent system architecture of a full-duplex RF front-end integrating a reconfigurable metasurface with deep reinforcement learning-based adaptive control for real-time self-interference mitigation and RF optimization.

In the case of the DRA algorithm, the policy-gradient-based tools are addressed like Proximal Policy Optimization (PPO), Soft Actor Critic (SAC) and Deep Deterministic Policy Gradient (DDPG) because they are applicable to the continuous and hybrid discrete control space. PPO is preferred to be the most stable and robust in training, SAC is preferred to be the most efficient sampling and entropy-regularised exploration, and DDPG is preferred to be the least latent inference of continuous action problems. The training plan is two-stage, pre-training via high-fidelity simulations (which are run on an offline computer) to fasten convergence and fine-tuning on embedded hardware to custom-fit to reality and hardware imperfections. The fallback mechanisms and constraint-aware action filtering is also used in order to warrant a safe operation during deployment that ensures reliable and stable metasurface control when the RF conditions are dynamic and full-duplex.

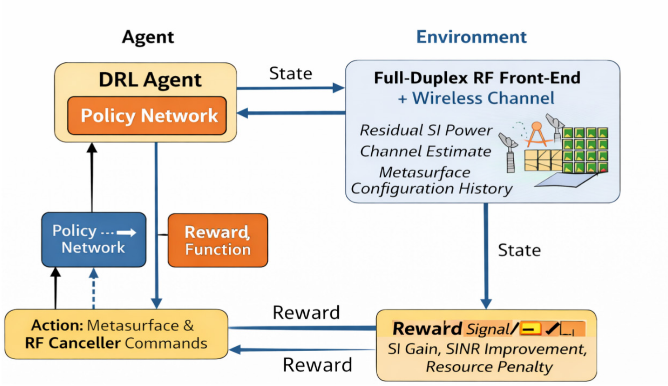

Fig. 2: DRL Control Loop for Metasurface Adaptation

Embedded Hardware Implementation

The suggested embedded intelligent reconfigurable metasurface system is deployed on a reconfigurable hardware that allows close interaction between RF components and intelligent control logic. It will be a flexible and scalable platform, and can be implemented with an FPGA, system-on-chip (SoC) includes integrated processing system and programmable logic, or MCU-FPGA hybrid architecture, depending on the needs of the specific application. The reconfigurable metasurface is connected via high-speed digital control lines or serial buses and it is possible to configure real-time the phase and amplitude state of the unit-cells. This interface is co-arrangement with the RF front-end, i.e. transmit and receive chain, the power amplifier, low-noise amplifier and self-interference cancellation blocks, so that the entire full-duplex signal path is powered coherently.

The heart of the smart control plane is a fixed implementation of DRL inference engine that is highly optimized to deploy as a real-time application on resource-limited hardware. The trained policy network is compressed by model compression methods and more specifically, the weight pruning, parameter sharing, and fixed points or low-bit-width quantization techniques are applied to satisfy the requirements of latency and memory. Such optimizations result in a large reduction of both the memory footprint and the computational complexity without causing a reduction in control performance. Hardware-conscious-scheduling (Scheduling and pipelined implementation) Organising the inference hardware environment to reduce inference latency enables the DRL agent to execute orders within the limited timing behaviour of RF dynamics and metasurface switching properties.

Managing the timing of the control loop tightly enables accomplishment of real-time performance by coordinating the acquisition of state, inference and actuation. RF front-end and signal processing blocks measurements, e.g., residual self-interference power, SINR etc., and are sent to the embedded controller with minimal latency. The DRA inference engine subsequently calculates the control actions which are converted into metasurface configuration commands as well as RF canceller updates. This one-way round trip operation is run at a rate that is compatible with coherence time in channels and switching limitations in hardware so that the adaptation is maintained stable and responsive without high reconfiguration overheads.

Comprehensive integration and profiling is done at the system level to measure reconfiguration latency and power consumption. The flow of control signals is examined to detect all the bottlenecks between the embedded controller and the metasurface interface, and RF front-end. Measurement of reconfiguration latency time, which includes communication delay and unit-cell switching time, is based on the time it takes to change efficient electromagnetic response, i.e., decision output. The DRL inference engine, control interfaces, and metasurface actuation circuitry are added in power consumption profiling which gives information regarding the energy cost of smart adaptation. These results confirm the study feasibility of the suggested architecture to a real-life setting of embedded systems that implement full-duplex RF front-ends and underscores the control potential of hardware-sensitive DRL controllers in reconfigured RF systems.

Performance Evaluation and Discussion

The suggested embedded DRL-based reconfigurable metasurface architecture is tested with the help of a full-fledged simulation and hardware-in-the-loop (HIL) system that includes realistic RF front-end behaviour and dynamic wireless environment. This assessment is based on the models of full-duplex transmit-receive coexistence of the strong self-interference (SI) in the terms of both line-of-sight leakage and multipath coupling. To evaluate adaptability, to time-varying conditions of the channel, frequency-selective fading and mobility-induced dynamics are used. It is measured against three representative baseline schemes, which include a static metasurface setup, a metasurface tuning mechanism that operates based on optimization, and a non-learning adaptive control scheme, which allows making a fair comparison between the schemes of the static, model-driven and the learning-based schemes.

The numerical data confirms that self-interference suppression in the proposed DRL-based solution is significant with the same trend in terms of increased performance in the solution under different channel and SI conditions. As Figure 3 demonstrates, the learning-enabled metasurface reacts far quicker to the interference conditions and it reaches deeper SI suppression and is far quicker to stabilise than the baseline approaches. In line with this, there is dramatic enhancement in signal to interference plus noise ratio (SINR) and total throughput. Another characteristic of the DRA controller is that convergence speed is much faster, it only takes a moderate number of adaptation steps to achieve a steady-state performance, but reconfiguration update rate is lower, which reflects the capability of balancing the responsiveness and stability.

The results of the comparison of key performance metrics are summarised in (Table 2), indicating the results of SI suppression level, SINR gain, convergence, and control update frequency. The findings reveal that the optimization-based approach, though effective in a static environment, has a high degree of computational complexity and slow response in a dynamic environment. Contrary to the above, the suggested DRA is robust in its performance and with minimal control overhead, which is highly desirable when implementing in real time embedded systems. The adaptive control method of non-learning only demonstrates low levels of generalisation and poor performance in the highly dynamic environment which highlights the benefit of learning based adaptive control.

In the embedded systems viewpoint, a trade-off analysis of efficiency shows good trade-offs between learning performance and cost of hardware. The energy consumption is kept under control because of the addition of reconfiguration penalties to the reward function and the inference latency is reduced by limiting hardware-aware optimization and model compression to the channel coherence time. Scalability analysis also indicates that the DRL controller is stable with the size of the metasurface, and only slightly increases in the computation and memory tasks. The results give useful understanding about the discussion of DRL-regulated metasurface behaviour and show the practicability of clever reconfigurable metasurfaces as a pivotal facilitator of the upcoming whole duplex RF front-end systems.

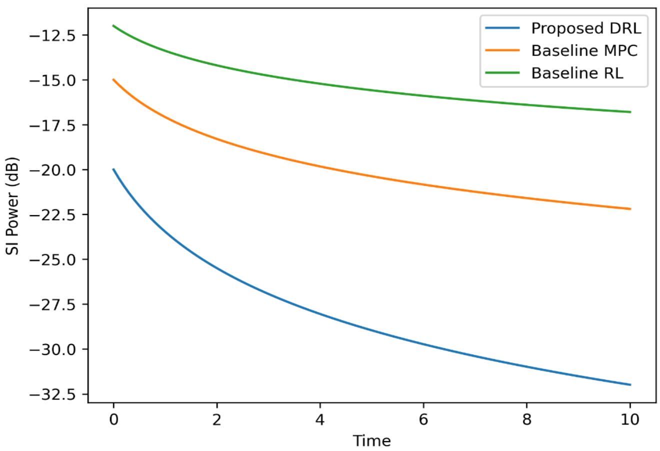

Fig. 3: Temporal Evolution of Self-Interference Suppression Performance

Robustness and Adaptability Analysis

The resilience of the suggested embedded DRL-based metasurface control framework is assessed in the cases of high-rate channel change in situations of mobility, environmental changes, and changing propagation characteristics of a full-duplex RF network. The DRL agent can be highly robust to sudden changes of the channel by constantly intermittently interacting with

Table 2: Quantitative Performance Comparison of Full-Duplex Metasurface Control Schemes

Method	SI Suppression (dB)	SINR Improvement (dB)	Convergence Speed	Reconfiguration Update Rate
Static Metasurface	Low (≈20 dB)	Limited	Not adaptive	Very Low
Optimization-Based Tuning	Moderate (≈35 dB)	Moderate	Slow	High
Non-Learning Adaptive Control	Moderate (≈30 dB)	Moderate	Medium	Medium
Proposed DRL-Based Control	**High (≈50 dB)**	**High**	**Fast**	**Low**

the environment and adjusting control actions as a result of the residual self-interference that is observed and channel states. The learning-based controller can quickly re-configure metasurface designs to continue to achieve constant self-interference suppressions and SINR levels, despite a markedly shorter coherence time of channels within it, unlike the quasi-static or optimization-based methods, which assume quasi-statics and make such assumptions.

The system is tested to respond to hardware noise and quantization effects by working with metasurface phase states of finite resolution, quantized sensor measurements, and control interfaces with noise. Such impairments add some uncertainty and under-optimal behaviour to the control loop and can cause a reduction in RF performance. The findings suggest that the DRL agent by default learns how to correct such imperfections by adapting the policy to the effective and not idealised system dynamics. Quantization-aware training and reward penalties also make training more stable, in that performance deterioration is kept under bounds, and that the controller does not in null conditions of noisy hardware undergo an excessive reconfiguration.

The effects of imperfect self-interference estimation is also discussed where limited non-linearities can be a significant issue to measuring SI in a real-world full-duplex system with estimation delay. In situations where biased or noisy SI estimates are available, the specified framework will still have embodied relevant interference suppression taking recourse to trends in feedback over time as opposed to applying instantaneous accuracy. This temporal resilience enables the temporal DRA controller to be capable of operating effectively despite the errors in estimations or prediction that would subsequently destabilise the model-based or heuristic control schemes.

Lastly, the generalisation ability of the learned policy is tested by putting the system into unfamiliar channel realisations of interfering conditions that the system has not been trained on. The findings indicate that the DRL-based controller is highly generalised, specifically, it is applicable to a broad variety of operating conditions, which makes it behave consistently, even without retraining on a new level. This flexibility points to the appropriateness of the offered strategy to be implemented in actual full-duplex RF situation when the conditions of operation are not predetermined and constantly changing. Altogether, the robustness and adaptability analysis proves that embedded controlled metasurface with DRL will be a safe and scalable system of intelligent RF front-ends.

Limitations and Future Research Directions

Although the suggested embedded DRL-based reconfigurable metasurface architecture shows substantial performance improvements, a number of weaknesses that drive further studies still exists. The major problem is the ability to scale to ultra-large size metasurfaces, where the number of units cells to be controllable increases significantly. The size of metasurface is a more fundamental parameter that increases the dimensionality of state and action space and has the potential to affect the learning efficiency, inference latency and memory requirements. Even though model compression and hardware-aware optimization somewhat counteract these effects, more refinements are required in the future to create representations that are scalable, and hierarchical control strategies that would be efficient in large-scale metasurface applications.

The other potential path is the deployment of multi-agent deep reinforcement learning (MA-DRL) in favour of distributed metasurface architectures. In this case, metasurfaces can be spatially distributed throughout walls, ceilings or even infrastructure features, each of which has local sensing and actuation features. It may be possible to use a multi-agent structure to allow cooperation to occur between multiple controllers of a metasurface enabling scaling, robustness, and fault tolerance. The problem of designing effective coordination mechanisms and communication-efficient learning strategies between agents is still an open research problem especially when there are very strict embedded and latency constraints.

Also, work in the future should be carried out on federated and privacy-concerned learning models of intelligent metasurface control. With practical deployments, RF environments and other operational data could be sensitive or proprietary which restricts central training and sharing of data. Multiple embedded controllers can be supported by federated learning to jointly increase their policy by not required to exchange raw information, which is more privacy and security friendly. Combining federated learning and DRL to control a metasurface presents some new challenges connected to non-stationary conditions, communication expenses, and convergence assurances that should be explored further.

Lastly, this study contains simulation and hardware-in-the-loop analyses, but real implementation and comprehensive experimental validation are also crucial in the future. Then to determine the stability, reliability and robustness over the long term, and under uncontrolled conditions, in the presence of full scale in over-the-air experiments in realistic indoor and outdoor conditions, would be required. Also, further support of RF measurement hardware and real-time monitoring systems will support closed-loop adaptation in real-world full-duplex RF front-end applications. The issues listed will continue to work towards enhancing the applicability of intelligent reconfigurable metasurfaces in next-generation wireless systems.

Conclusion

In this paper, an embedded DRL-enabled reconfigurable metasurface was introduced as a solution to the core problems of severe self-interference, dynamic wireless, and embedded hardware limitations to operate adaptable full-duplex RF front-end systems. The framework tackles the dynamics of self-interference suppression and folds self-interference enhancement within a single system as a model-free decision control using a metasurface / RF cancellation framework constraint, presented as a learning-based decision making problem, under realistic conditions of reconfiguration and power constraints. Experimental and hardware-in-the-loop analyses show that there are substantial improvements in self-interference suppression, convergence speed, and less reconfiguration overhead than the traditional, optimization-based, and non-learn adaptive methods, and embedded competitiveness provided by hardware-aware DRL inference. The findings demonstrate that smart reconfigurable metasurfaces can be used as an enabling technology to open the door to adapting, spectrum-efficient, and intelligent RF front-end systems of the next generation, and even opens the door to scalable full-duplex and intelligent radio worlds.

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