MTP Report Short

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Abstract

This work explores the use of intelligent reflecting surfaces (IRS) to improve wireless communication in non-line-of-sight scenarios. We study the complexity of traditional optimization methods such as Alternating Optimization (AO) and Projected Gradient Method (PGM), and explored the idea of predicting IRS phase shifts and beamforming vectors from channel gains using machine learning-based approaches. Various prediction strategies are evaluated for both single-user and multi-user setups. Our results show a significant reduction in algorithmic iterations for single-user scenarios, with further complexity reduction that can be achieved through phase quantization and IRS element grouping, enabling practical deployment with with trade off loss in performance with computational complexity.

Notation

In this report, the following notation is used:

- N_{ris}: Number of Intelligent Reflecting Surface (IRS) elements.
- N_{t}: Number of base station antennas.
- N_{r}: Number of receiver antennas per user.
- K: Number of users.

Intelligent Reflecting Surfaces (IRS) are a cost- and energy-efficient solution to enhance wireless communication in non-line-of-sight conditions. They achieve this by intelligently adjusting the phase shifts of their reflecting elements to create favorable propagation paths. In this work, we address the joint optimization of IRS phase shifts and transmit beamforming vectors, which is known to be a non-convex and computationally intensive problem due to their interdependency.

We begin with the Alternating Optimization (AO) algorithm as presented in [GLCL20] has computational complexity $\mathcal{O}(I_0(2KNirsNt + KNt^2 + K^2Nirs^2))$ and relies on random phase initialization. The idea was to reduce the outer iterations by predicting the IRS phase vector and beamforming vector suing neural network that from channel gains to find a better starting point for the algorithm which will result in faster convergence. Three learning-based strategies are tested: (i) joint prediction of both vectors, (ii) separate prediction, and (iii) sequential prediction—beamforming first, followed by phase prediction and results are shown in the Figure 1. Among these, the third approach performs best in the single-user case by reducing the number of required AO iterations. However, for two-user scenarios, all learning methods struggle and behave comparably to random initialization.

To further reduce complexity and improve learning feasibility, we adopt the Projected Gradient Method (PGM) as proposed in [PTDRF21], which converges faster than AO. We consider a wireless communication system whose aerial view is depicted in figure 2. We then quantize the IRS phases into various discrete levels and found that after 32 bit quantization there is no significant loss rate. Quantization could help reduced learning complexity for ML models. It can also help use turn the regression problem to classification-based learning problem for phases but it may increase model complexity as we would need separate classification model for each element separately. The performance loss from

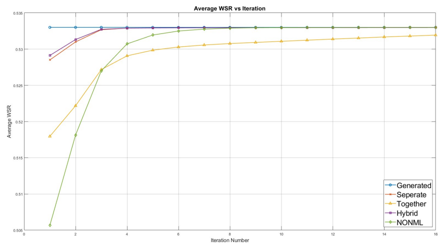

Fig. 2.(a)

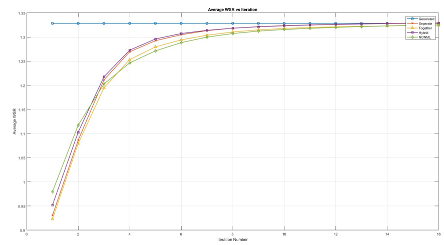

Fig. 2.(b)

Figure 1: WSR vs Number of iterations based on starting point for AO algorithm. (a): $K = 1$, $Nt = 2$, $Nr = 1$,Nris $= 25.(b)$:K $= 2$,Nt $= 4$,Nr $= 1$, $Nris = 50$

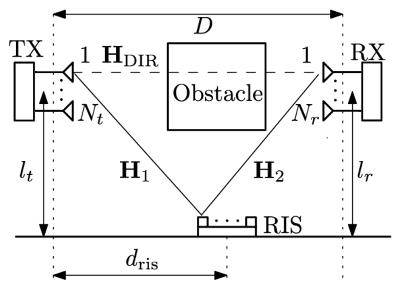

Figure 2: Ariel view of considered communication system for PGM

quantization can be seen in Figure 3(a) and similar trend was being followed buy all follow up cases when quantization is used. In addition, IRS elements are grouped into square patches, reducing the number of variables to optimize but it will also result in performance loss as the patch size increase, depicted in figure 3(b). Combining both the techniques leads to a decrease in achievable rate but can offer a good trade-off between performance and complexity of problem for machine learning models.

We also extend our setup to more complex scenarios: multiple IRS with a single user in which rate increase in both cases when tow IRS act independently or dependently as show in figure 4(a), a single IRS with multiple users (assuming successive interference cancellation at the receiver), result are shown in figure 4(b), multiple IRS with multiple users, from results in figure 5(a) we can see that rate increase as the one more IRS came into the picture. [ZYZ21].

All simulations assume perfect channel state information (CSI) at the transmitter and IRSs located in the far-field region.

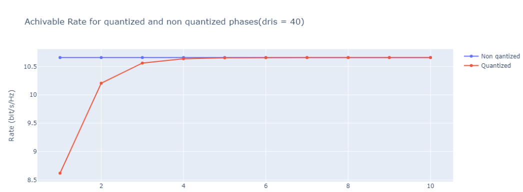

Fig. 3.(a)

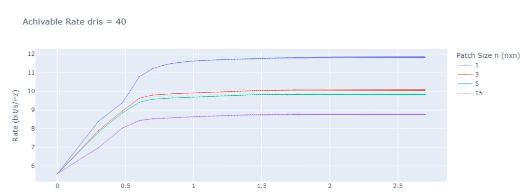

Fig. 3.(b)

Figure 3: $K = 1$, $Nt = 4$, $Nr = 8$, $Nris = 225$. (a): Achievable Rate vs nubmer of quntization bits. (b): Achievable Rate vs number of iterations of PGM for given patch size

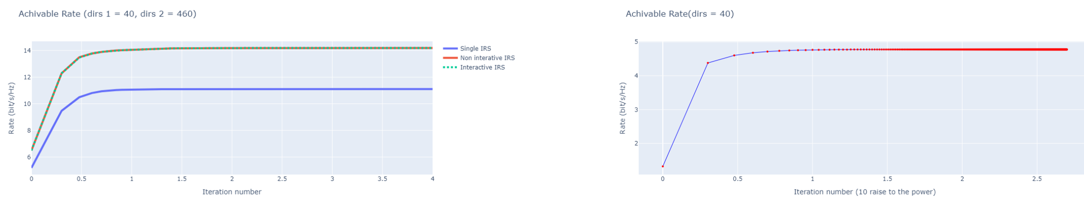

Fig. 4.(a) Fig. 4.(b)

Figure 4: Achievable Rate vs Number of iterations of PGM. (a): $K = 1$, $Nt = 4$, $Nr = 8$, $Nris1 = 225$, $Nris = 225$. (b): Achievable Rate vs number of iterations of PGM $K = 2$, $Nt = 1$, $Nr = 1$, $Nris = 225$

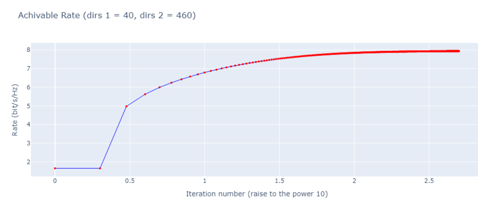

Fig. 1.(a)

Figure 5: Achievable Rate vs Number of iterations of PGM. Fig. 1.(a): $K = 2$, $Nt = 4$, $Nr = 8$, $Nris1 = 225$, $Nris = 225$.

References

[GLCL20] Huayan Guo, Ying-Chang Liang, Jie Chen, and Erik G. Larsson. Weighted sum-rate maximization for reconfigurable intelligent surface aided wireless networks. *IEEE Transactions on Wireless Communications*, 19(5):3064–3076, 2020.

[PTDRF21] Nemanja Stefan Perović, Le-Nam Tran, Marco Di Renzo, and Mark F. Flanagan. Achievable rate optimization for mimo systems with reconfigurable intelligent surfaces. *IEEE Transactions on Wireless Communications*, 20(6):3865–3882, 2021.

[ZYZ21] Beixiong Zheng, Changsheng You, and Rui Zhang. Double-irs assisted multi-user mimo: Cooperative passive beamforming design. *IEEE Transactions on Wireless Communications*, 20(7):4513–4526, 2021.