Convex Optimization Project Proposal - MMSE Based MIMO Channel Estimator Via Primal-Dual Optimization Mehthod with Neural Network

312510199 Jing-Hao, Li and 312510197 Zhao-Jie, Luo
Advisor: Professor Carrson C. Fung
Apr. 24, 2024

Introduction

We consider a communication system which contains one transmitter and one receiver, and they communicate with each other through a interference channel with Gaussian noise. There are multiple antennas in both transmitter and receiver, implies that it's a MIMO system.

We are interested in finding the channel coefficients so that we can deal with this interference channel by using some methods in the precoder, then we can alleviate the interference caused by the channel.

We can send some pilot signals during a time slot, receive these signals which pass through the channel and effected by additive Gaussian noise, then the system model can be written in this form:

$$\mathbf{Y} = \mathbf{H}\mathbf{X} + \mathbf{W}$$

Where $\mathbf{X}$ is the transmitted pilot signal, $\mathbf{W}$ is the additive Gaussian noise, $\mathbf{Y}$ is the recieved signal, and $\mathbf{H}$ is the channel coefficients that we want to estimate.

Proposed Approach

We can control $\mathbf{X}$, which is the pilot signal, to have some properties. The mostly used is to let it to be concatenated identity matrix.

1) If the pilot signal $\mathbf{X}$ is a square matrix, which means that it is just a identity matrix, then the estimation $\widehat{\mathbf{H}}$ could be $\mathbf{Y}\mathbf{X}^{-1}$, which is equal to $\mathbf{Y}$.
2) If $\mathbf{X}$ is a nonsquare concatenated identity matrix, we can obtain $\widehat{\mathbf{H}} = \mathbf{Y}$ multiply the pseudo inverse of $\mathbf{X}$ by using least square method.
3) To improve performence, [1] suggests that we can use MMSE based primal-dual optimization method with neural network to estimate $\mathbf{H}$. We want to obtain the minimun mean square error between $\mathbf{H}$ and $\widehat{\mathbf{H}}$. Then we reformulate the problem into epigraph form. We also use parameterize $\widehat{\mathbf{h}}$, which can be a MLP [3], so that we can obtain the primal and dual function and thus we can update the primal and dual variables by gradient descent and ascent via policy gradient [3] until it converges.
4) However, fully connected neural networks are impractical to both train and implement for large scale networks, as their size grows quickly with network size [2], we can use graph neural network [4]–[6] to be our parameterized channel estimator to see how it works under large number of transmitter and receiver antennas.

We can compare the performences with these approaches under different SNR and network size.

References

[1] Carrson C. Fung, and Dmytro Ivakhnenkov, "Model-Driven Neural Network Based MIMO Channel Estimator"

[2] M. Eisen and A. Ribeiro, "Large scale wireless power allocation with graph neural networks," *Proc. of the 2019 IEEE 20th Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, pp. 1-5, 2019.

[3] M. Eisen, C. Zhang, L.F.O. Chamon, D.D. Lee and A. Ribeiro, "Learning optimal power allocations in wireless systems," *IEEE Trans. on Signal Processing*, vol. 67(10), pp. 2775-2790, May 2019.

[4] M. Eisen and A. Ribeiro, "Optimal wireless resource allocation with random edge graph neural networks," *IEEE Trans. on Signal Processing*, vol. 68, pp. 2977-2991, 2020.

[5] N. NaderiAlizadeh, M. Eisen and A. Ribeiro, "State-Augmented learnable algorithms for resource management in wireless networks," *IEEE Trans. on Signal Processing*, vol. 70, pp. 5898-5912, Dec. 2022.

[6] N. NaderiAlizadeh, M. Eisen and A. Ribeiro, "Learning resilient radio resource management policies with graph neural networks," *IEEE Trans. on Signal Processing*, volo. 71, pp. 995-1009, Mar. 2023.