Quantum Model for Hybrid Beamforming Optimization

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Abstract

Hybrid beamforming has become a technique that reduce high implementation cost and energy by combining the digital and analog beamforming. This study utilize quantum based approached for hybrid beamforming optimization. Specifically, a quantum neural networks is used to optimized the hybrid beamforming given by acquired channel estimation. Subsequently, the optimization results are used to maximizing the achievable sum – rate and to reduce the complexity.

Keywords – Hybrid Beamforming, quantum neural networks, wireless systems.

Ⅰ. Introduction

Beamforming is a technique in wireless communication to steer and concentrate the transmit signal into beam from base station to the target user. Multiple antennas are required for beamforming, because it will be affected to the produce of beam. At present, there are three forms of beamforming, analog beamforming, digital beamforming, and hybrid beamforming. The hybrid beamforming proposed [1] to handle the limitation of both analog and digital beamforming. It's required less hardware, cost, and can provide near optimal performance compared to the digital beamforming.

As exhibited in prior work [2] a machine learning – based approach artificial neural networks (ANN) can be employed to obtain the optimization of hybrid beamforming. Even, on this work [3] it's already used the deep learning approached. This kind approaches are used to reduce the complexity of the optimization problem [3].

There's one model that combine the ANN with quantum computing called quantum neural networks (QNN). QNN has offer more advantages [4] in wireless communication problem rather than classical ANNs, it's including on optimization problem.

In this paper, the idea of quantum neural networks is presented for hybrid beamforming optimization.

Ⅱ. Method

Consider a communication scenario with a single ground base station serving a number K receivers for downlink case. In addition, let N_{Tx} be the numbers of transmitting antennas, The N_{RF} as number of the RF ch ain, N_s as number of data streams, while $N_{Rx}^{(k)}$ is the number of receiving antennas for the kth user. Without loss of generality, let considers $N_{Rx}^{(1)} = N_{Rx}^{(k)} = N_{Rx}^{(K)} = N_{Rx} = 1$.

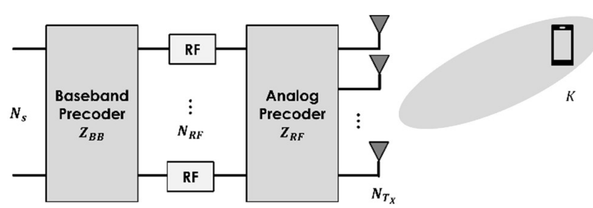

Fig. 1. System Model

The transmitter employs hybrid precoding to allow beam steering while reducing the number of RF chain. Let us define $\boldsymbol{z}_{BB} \in \mathbb{C}^{N_{RF}\times N_s}$ and $\boldsymbol{z}_{RF} \in \mathbb{C}^{N_{Tx}\times N_{RF}}$ baseband precoder and analog precoder, respectively. The transmitted signal can be written as

$$\boldsymbol{x} = \boldsymbol{z}_{RF}\boldsymbol{z}_{BB}\boldsymbol{s}\,, \tag{1}$$

where $\boldsymbol{s} \in \mathbb{C}^{N_s\times 1}$ is a vector of transmitted symbols. For the received signal is

$$\boldsymbol{y}_k = \boldsymbol{h}_k^H \boldsymbol{z}_{RF}\boldsymbol{z}_{BB,k}\boldsymbol{s}_k + \boldsymbol{h}_k^H \sum_{j\neq k} \boldsymbol{z}_{RF}\boldsymbol{z}_{BB,j}\boldsymbol{s}_j + \boldsymbol{n}_k\,, \tag{2}$$

Where $\boldsymbol{n}_k$ represented as noise and H subscript letter denotes Hermitian transpose. The Rayleigh fading coefficient [5] of the k-th user can be expressed as

$$\boldsymbol{h}_k = \sqrt{\frac{N_{Tx}N_{Rx}}{L}}\sum_{l=1}^{L}\boldsymbol{\beta}_l\, \boldsymbol{a}_{Tx}(\theta^{Tx})^H \boldsymbol{a}_{Rx}(\theta^{Rx}), \quad (3)$$

where $\boldsymbol{\beta}_l \sim \mathcal{CN}(0,1)$, $\theta^{Tx} \sim \mathcal{U}\left(-\frac{1}{2},\frac{1}{2}\right)$, $\theta^{Rx} \sim \mathcal{U}\left(-\frac{1}{2},\frac{1}{2}\right)$, and L denotes the complex path gain, angle of departure (AoD), angle of arrival (AoA), and number of paths, respectively. In addition, the antenna steering vector for both transmit and receive are given by

$$\boldsymbol{a}_{Tx}(\theta^{Tx}) = \frac{1}{\sqrt{N_{Tx}}}\left[1, e^{-j\frac{2\pi}{\lambda}d\cos(\theta^{Tx})}, \ldots, e^{-j\frac{2\pi}{\lambda}d(N_{Tx}-1)\cos(\theta^{Tx})}\right]^T, \quad (4)$$

$$\boldsymbol{a}_{Rx}(\theta^{Rx}) = \frac{1}{\sqrt{N_{Rx}}}\left[1, e^{-j\frac{2\pi}{\lambda}d\cos(\theta^{Rx})}, \ldots, e^{-j\frac{2\pi}{\lambda}d(N_{Rx}-1)\cos(\theta^{Rx})}\right]^T, \quad (5)$$

where $d = \frac{\lambda}{2}$ is the distance between one antenna to other antenna and λ represented as signal wavelength.

To see the performance of the hybrid beamforming, let us define the achievable sum – rate, which can be expressed as

$$R_{sum} = \sum_{k=1}^{K}\log_2\left(1 + \frac{\left|\boldsymbol{h}_k^H \boldsymbol{z}_{RF}\boldsymbol{z}_{BB,k}\right|^2}{\sigma^2 + \sum_{j\neq k}\left|\boldsymbol{h}_k^H \boldsymbol{z}_{RF}\boldsymbol{z}_{BB,j}\right|^2}\right), \quad (6)$$

where σ^2 is noise power, $\log(\cdot)$ is logarithm operator and $|\cdot|$ indicate the absolute value. For the optimization problem is written as

$$\max_{\boldsymbol{z}_{RF},\boldsymbol{z}_{BB}} R_{sum} \quad (7a)$$

$$s.t.\ \left|[\boldsymbol{z}_{RF}]_{i,j}\right| = 1, \forall\, i,j \quad (7b)$$

$$\|\boldsymbol{z}_{RF}\boldsymbol{z}_{BB}\|_F \leq 1. \quad (7c)$$

The first constraint of Eq. (7b) is the modulus constraint for phase shifter in analog precoder, and the second constraint of Eq. (7c) to satisfies the power constraint with normalized power. The $\|\cdot\|_F$ represents the Frobenius norm.

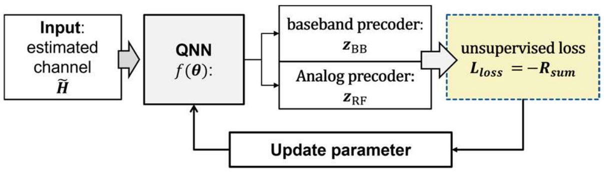

Fig. 2. Proposed Method

As shown in figure 2, the input will be generated estimated channel that through to the QNN. The weight of baseband and analog precoder are the output of model. Next, calculated the loss and update the model for next iteration, the model then learns to optimize $\boldsymbol{z}_{BB}$ and $\boldsymbol{z}_{RF}$.

Ⅲ. Conclusion

Hybrid beamforming is a technique that reduce high implementation cost and energy by reducing the number of RF chains and improve the achievable sum rate of the system. In this paper, it can be shown that the QNN can be used or feasible for hybrid beamforming optimization problem. The advantages of QNN over the classical ANN will be a performance different between this two.

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REFERENCES

[1] Xinying Zhang, A. F. Molisch and Sun-Yuan Kung, "Variable-phase-shift-based RF-baseband codesign for MIMO antenna selection," in IEEE Transactions on Signal Processing, vol. 53, no. 11, pp. 4091-4103, Nov. 2005.

[2] M. S. Aljumaily and H. Li, "Hybrid Beamforming for Multiuser MIMO mm Wave Systems Using Artificial Neural Networks," 2021 International Conference on Advanced Computer Applications (ACA), Maysan, Iraq, 2021.

[3] P. Zhang, L. Pan, T. Laohapensaeng and M. Chongcheawchamnan, "Hybrid Beamforming Based on an Unsupervised Deep Learning Network for Downlink Channels With Imperfect CSI," in IEEE Wireless Communications Letters, vol. 11, no. 7, pp. 1543-1547, July 2022.

[4] S. J. Nawaz, S. K. Sharma, S. Wyne, M. N. Patwary and M. Asaduzzaman, "Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future," in IEEE Access, vol. 7, pp. 46317-46350, 2019.

[5] A. Alkhateeb, O. El Ayach, G. Leus and R. W. Heath, "Channel Estimation and Hybrid Precoding for Millimeter Wave Cellular Systems," in IEEE Journal of Selected Topics in Signal Processing, vol. 8, no. 5, pp. 831-846, Oct. 2014.