Zero – Forcing Hybrid Precoding with Quantum Neural Network Optimization

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Abstract

In this paper, quantum neural network is presented to optimize hybrid precoding based on zero – forcing with unsupervised learning. Quantum neural network will be utilize to produce the optimize variables for analog and digital precoding that will combine into hybrid precoding . The aim of optimization is to maximize the achievable spectral efficiency.
Keywords: Hybrid precoding, quantum neural network, wireless communication.

Ⅰ. Introduction

To solving the limitation of analog and digital precoding in wireless communication systems, hybrid precoding [1] is proposed as the one of the solution. When compared to digital precoding, hybrid precoding provide fewer expenses while providing near – optimal solution. This major impact on performance, produce many research surrounding hybrid precoding [2][3]. Several studies [4][5] have explored the development of neural network and quantum computing as quantum neural network (QNN). This paper employs unsupervised learning QNN optimization for hybrid precoding with zero – forcing criteria.

Ⅱ. Method

Consider a MIMO system with single user for downlink scenario shown in Fig. 1. Let the $N_s, N_{Tx},$ and N_{Rx} denoted as number of data streams, number of transmitter antennas, and number of receiver antennas. The $\mathbf{F}_{\mathrm{BB}} \in \mathbb{C}^{N_{RF} \times N_s}$ and $\mathbf{F}_{\mathrm{RF}} \in \mathbb{C}^{N_{Tx} \times N_{RF}}$ define as digital and analog precoding, respectively.

Geometric channel using a uniform linear array (ULA) antenna [6] is considered as the channel matrix, which can be shown as:

$$\boldsymbol{H} = \sqrt{\frac{N_{Tx} N_{Rx}}{N_{path}}} \sum_{l=1}^{N_{path}} \boldsymbol{\beta}_l \boldsymbol{A}_{Tx}(\vartheta^{Tx})^H \boldsymbol{A}_{Rx}(\vartheta^{Rx}), \tag{1}$$

where the following distributions are assumed $\boldsymbol{\beta}_l \sim \mathcal{CN}(0,1)$, $\vartheta^{Tx} \sim \mathcal{N}(0,2\pi)$, $\vartheta^{Rx} \sim \mathcal{N}(0,2\pi)$ to be the complex path gain angle of departure and arrival (AoD and AoA). The N_{path} is number of paths. In addition, the antenna steering vectors for the transmit and receive are given as follows:

$$\boldsymbol{A}_{Tx}(\theta^{Tx}) = \frac{1}{\sqrt{N_{Tx}}}[1, e^{-j\frac{2\pi}{\lambda}d\cos(\theta^{Tx})}, \dots, e^{-j\frac{2\pi}{\lambda}d(N_{Tx}-1)\cos(\theta^{Tx})}]^T, \tag{2}$$

$$\boldsymbol{A}_{Rx}(\theta^{Rx}) = \frac{1}{\sqrt{N_{Rx}}}[1, e^{-j\frac{2\pi}{\lambda}d\cos(\theta^{Rx})}, \dots, e^{-j\frac{2\pi}{\lambda}d(N_{Rx}-1)\cos(\theta^{Rx})}]^T, \tag{3}$$

where $d = \frac{\lambda}{2}$ can be define as distance between each antenna. Let λ denotes the signal wavelength.

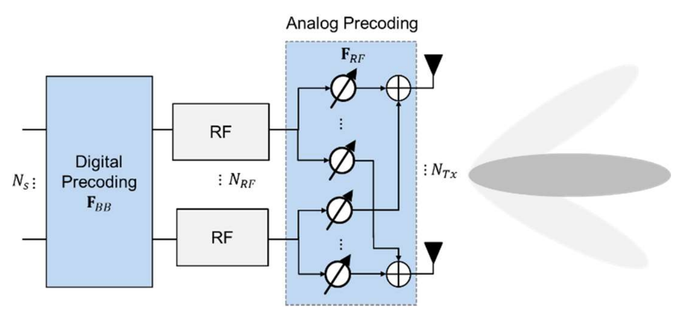

Fig. 1. System Model.

As illustrated in Fig. 2. First, generate the channel matrix $\boldsymbol{H}$ as dataset. Then, this channel matrix will be input QNN process to get three optimize variables, one for analog precoding γ_{RF} and two for digital precoding $\gamma_{BB}^{[scale]}, \gamma_{BB}^{[shift]}$ [7][8]. The analog precoding $\mathbf{F}_{\mathrm{RF}}$ can be obtained directly from antenna steering vector, and the other hand, digital precoding $\mathbf{F}_{\mathrm{BB}}$ can be obtained based on the zero – forcing criteria.

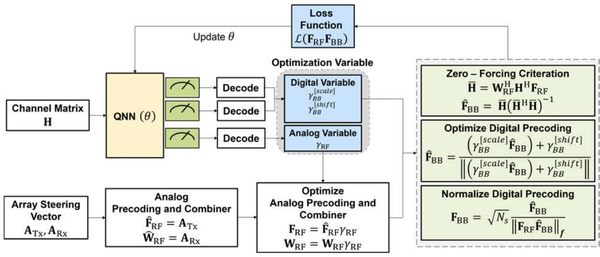

Fig. 2. Proposed Method.

The aim of this optimization is maximize the spectral efficiency [9] that can be expressed as

$$S = \log_2\left(\left|\boldsymbol{I}_{N_{Rx}} + \frac{\rho}{N_s}\mathbf{H}\mathbf{F}_{RF}\mathbf{F}_{BB} \times \mathbf{F}_{BB}^{*}\mathbf{F}_{RF}^{*}\mathbf{H}^{*}\right|\right), \qquad (10)$$

where $\mathbf{I}_{N_s}$ is identity matrix, and ρ is signal − noise − ratio and is $(\cdot)^*$ hermitian operation. The loss function hybrid precoding can be expressed as $\mathcal{L} = -S$.

Ⅲ. Result and Conclusion

The simulation shown in Fig. 3 from IBM Qiskit [10] as quantum computation platform. that been used are N_s = 4, N_{Tx} = 16, N_{Rx} = 4, N_{RF} = 4, N_{path} = 10, $N_{iteration}$ = 100, N_{data} = 50, with $learning\ rate$ = 10^{-4}.

This paper considered a scenario with single user in MIMO hybrid precoding based on zero – forcing criteria with QNN optimization. Result shown that QNN can enhance and feasible to be used as optimization factors in hybrid precoding problem. For future work, other algorithms or optimization factors can be employ to QNN.

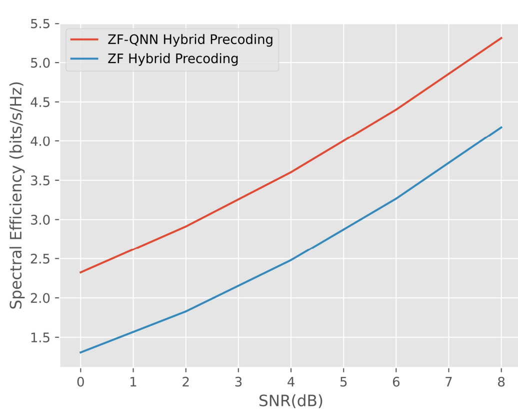

Fig. 3. Spectral Efficiency Result.

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