Energy Efficiency Hybrid Precoding for UAV Inspection Communication System

LI Minzheng¹, ZHAI Jiaqing*¹

¹School of Electronic Information Engineering, Shanghai Dianji University, Shanghai 201306, China
*Corresponding author’s e-mail: limz@sdju.edu.cn

Abstract. In order to reduce the communication power consumption during UAV power line inspection, a energy efficiency hybrid recoding scheme based on one phase shifter is proposed in its communication subsystem. The solution is realized by using a partially connected hybrid precoder architecture in the UAV communication terminal, and using a beam combiner at the wireless network access point. At the same time, in order to reduce the complexity of hybrid precoding and combiner beam optimization design, convolutional neural networks are used to dynamically design and select the optimized beam required for UAV inspection and communication. Under the premise of efficiency, the communication energy efficiency can be improved as high as possible, thereby effectively improving the battery life cycle and cruise time of the UAV. The simulation results show that, compared with the manifold optimization and orthogonal matching pursuit algorithms, the proposed algorithm can significantly improve the energy efficiency of communication coding and battery life cycle.

1. Introduction

With the development of smart grid, unmanned aerial vehicle inspections have higher bandwidth requirements. The 5G UAV Application White Paper released by the IMT-2020 (5G) Promotion Group pointed out that the large bandwidth, high reliability, and low latency communication provided by 5G technology can well meet the application requirements of UAV inspection.

However, the battery capacity of the UAV is limited, and the excessive communication power consumption will cause the UAV inspection operation time to be limited. In traditional MIMO systems, each antenna usually requires a dedicated radio frequency chain, which not only brings excessive hardware costs and complexity, but also leads to unbearable high energy consumption. Hybrid precoding[1] proposed that it can effectively reduce the number of radio frequency chains and power consumption[2], but for UAV inspection communication, the power consumption is still too high.

At present, some hybrid precoding methods optimized for energy efficiency have been proposed in the UAV communication scenario to reduce power consumption. Literature [3] studies the massive MIMO hybrid precoding scheme assisted by UAV, and proposes trajectory optimization and power allocation methods while meeting user rate requirements. Although it achieves higher energy efficiency, the calculation is too complicated. In reference [4], a hybrid precoding architecture based on lens antenna array for UAV downlink communication link is proposed. The optimal precoding matrix is solved by using cross entropy optimization, and higher energy efficiency is obtained. However, adaptive selection network needs to be deployed in the simulation domain to achieve higher complexity. Literature [5] decomposes the multi-element joint optimization problem of the joint precoding design of the UAV transmitter and receiver into the optimization solution of sub-problems,
which can achieve higher energy efficiency and spectrum efficiency, but due to the high computational complexity, hard to accomplish.

For this reason, a hybrid precoding scheme using a partial connection structure is proposed, and the quantization accuracy of the phase shifter is only 1 bit, so as to further reduce power consumption and improve the energy efficiency of UAV communication[6]. Then, based on this, under the premise of limited power consumption, seek a precoding scheme that maximizes the rate. In order to reduce the complexity of the optimization iterative algorithm, a convolutional neural network framework is used to optimize the design of the analog precoder and combiner at both ends of the transceiver. The simulation results show that the energy efficiency of the proposed hybrid precoding scheme based on a phase shifter is higher than that of the hybrid precoding method under the high-precision full-link architecture commonly used at present. At the same time, due to the optimization method of the convolutional neural network, the computational complexity is also lower.

2. System model

2.1. System specification

Assume that the UAV is equipped with a Uniform Planar Antenna Array with \( N_T = M_1 \times N_1 \) antennas, and the wireless access node is equipped with a UPA with \( N_R = M_2 \times N_2 \) antennas.

![Figure 1 Millimeter-wave massive MIMO system model at the transmitter and receiver](image)

As shown in Figure 1, UAV communication terminal uses a hybrid precoder and a beam combiner at the wireless network access node. In order to reduce communication power consumption, a partial connection structure is adopted. Each radio frequency chain is only connected to \( \frac{N_T}{N_R} \) antenna arrays, and the quantization accuracy of the phase shifter is only 1 bit. Compared with fully connected structure, it can effectively reduce the number of phase shifters and power consumption, and is dedicated to energy-efficient communication while obtaining the highest possible transmission rate.

In the UAV communication terminal, \( N_S \) data streams are respectively processed by the baseband precoder \( F_{BB} \) and the analog precoder \( F_{RF} \) and sent to the wireless network access node, then the transmitted signal can be expressed as \( BB_RF s \). \( s \) is the desired symbol vector, and the analog precoder is a unitary matrix with equal norm elements[7]. The transmitter has a power limit of \( \| F_{RF} F_{BB} \|_0 = N_S \). The wireless network access node receives the signal:

\[
y_i = \sqrt{\rho H F_{RF} F_{BB} s} n
\]  

(1)

Where \( \rho \) is the average received power. The size of \( n \) is \( N_R \times 1 \) which means that the compound additive white Gaussian noise of Gaussian distribution[8], \( H \) is the channel transmission matrix, and \( I_{N_R} \) is the identity matrix[9].

The signal received at the receiving end is processed by the combiner as:

\[
y = \sqrt{\rho W_{RF} W_{BB}} H F_{RF} F_{BB} s + W_{RF} W_{BB} n
\]  

(2)
Where $W_{\text{RF}}$ represents an analog combiner, $W_{\text{BB}}$ is a baseband combiner, and $(\cdot)\dagger$ represents the conjugate transpose of the matrix.

During UAV inspection, the flight speed is slow ($\approx 30\text{km/h}$) and the power transmission line is high (30-50m), the communication link is mainly line-of-sight path. Assuming that the number of scatterers between the UAV and the receiving end is $L$, the channel between the two can be expressed as:

$$H = \frac{N_t N_r}{L} \sum_{l=1}^{L} \alpha_l \phi_l(\theta_l^d) \phi_l(\theta_l^a)$$

(3)

Where $\alpha_l, \phi_l(\theta_l^d)$ and $\phi_l(\theta_l^a)$ respectively represent the $l_{th}$ path complex gain coefficient and the pitch angle of the angle of departure, and the angle of arrival. $\alpha_l(\phi_l^d, \theta_l^d)$ and $\alpha_l(\phi_l^a, \theta_l^a)$ denote the response vector of the UAV and the antenna array at the receiving end respectively.

### 2.2. Problem description

Based on the hybrid precoding under a phase shifter partial connection architecture, each RF chain is only connected to a sub-antenna array containing $N_t/N_R$ antennas, and the energy consumed can be expressed as:

$$P_{\text{one-bit-sum}} = P_t + N_R P_{\text{RF}} + N_t P_{\text{BB}}$$

Where $P_t$ represents the transmit power, $N_R$ represents the number of RF links, $P_{\text{RF}}$ and $P_{\text{BB}}$ represent the energy consumption of the RF link and baseband precoder respectively, and $P_{\text{one-bit}}$ is the energy consumed by a phase shifter, which is only 5mW[11].

The system and rate achieved by hybrid precoding are expressed as:

$$R = \log_2 \left( |I_{\text{in}} + \frac{\sigma^2}{N_S} W_{\text{RF}} W_{\text{BB}} \times F_{\text{RF}} F_{\text{BB}}^\dagger H^\dagger W_{\text{RF}} W_{\text{BB}}| \right)$$

(5)

Where $\sigma^2$ is the covariance matrix of the noise term[12].

The energy efficiency is defined as the rate to the total power consumption[13]:

$$\eta = \frac{R}{P_{\text{total}}}$$

(6)

In the hybrid precoding based on the partial connection structure of a phase shifter, energy consumption is significantly lower than the energy consumption based on the full connection of the high-precision phase shifter. Based on this, under the premise of limited power consumption, a hybrid precoding scheme that maximizes the rate is sought to improve the energy efficiency of hybrid precoding as much as possible. In order to maximize the system and rate, the design of a hybrid precoding and combiner can be expressed as:

$$\{\tilde{F}_{\text{RF}}, \tilde{F}_{\text{BB}}, \tilde{W}_{\text{RF}}, \tilde{W}_{\text{BB}}\} = \arg \max_{F_{\text{RF}}, F_{\text{BB}}, W_{\text{RF}}, W_{\text{BB}}} \frac{R}{P_{\text{total}}}$$

subject to: $F_{\text{RF}} \in F, W_{\text{RF}} \in W$,

$$\|F_{\text{RF}} F_{\text{BB}} W_{\text{RF}} W_{\text{BB}}\| = N_t$$

(7)

Where $\| \cdot \|$ is the Frobeinus norm of the matrix, $F$ and $W$ is a feasible set of precoder and combiner.

### 3. Optimal hybrid beamforming coding acquisition

First define the array response feasible set $F$ and $W$. The analog precoder and combiner $F_{\text{RF}}$ and $W_{\text{RF}}$ are related to the array response $\alpha_l(\Theta_l^{d/j}), \alpha_l(\Theta_l^{a/j})$ through a linear transformation. Therefore, the set of feasible analog precoders can be written as $F_{\text{RF}} = \{F_{\text{RF}1}, \ldots, F_{\text{RF}Q}\}$, $F_{\text{BB}} = \alpha_l(\Theta_l^{a/j})$, $q = 1, \ldots, Q$. $i=1, \ldots, N_c; j=1, \ldots, N_{\text{ray}}, N_c$ indicates the number of scattering clusters, $N_{\text{ray}}$ indicates the number of paths.

The joint design problems of hybrid precoder and combiner are as follows:

$$\overline{F}_{\text{RF}} = \arg \max_{q} \log_2 \left( |I_{\text{in}} + \frac{\sigma^2}{N_S} W_{\text{RF}} W_{\text{BB}} \times F_{\text{RF}} F_{\text{BB}}^\dagger H^\dagger W_{\text{RF}} W_{\text{BB}}| \right)$$

s.t. $F_{\text{RF}} = F_{\text{RF}q}, W_{\text{RF}} = W_{\text{RF}q}, F_{\text{BB}} = (F_{\text{RF}} F_{\text{RF}})^{-1} F_{\text{RF}}^\dagger F_{\text{RF}}^\dagger, W_{\text{BB}} = (W_{\text{RF}} W_{\text{RF}})^{-1} (W_{\text{RF}} W_{\text{RF}})^{-1}$

(8)
Where, $\tilde{q}_f, \tilde{q}_w$ is the index number that provides the maximum sum rate in the feasible set, and $\Lambda$ is the covariance of the array. $F^{opt}$ and $W^{opt}$ is the best baseband precoder and combiner, which can be obtained from the singular value decomposition of the channel matrix.

The solution of formula (8) is complicated. In order to reduce the complexity, the precoder ($F_{RF}$ and $F_{BB}$) and the combiner ($W_{RF}$ and $W_{BB}$) can be estimated separately, thus reducing the complexity from $O(Q_F, q_F) + O(Q_W, q_W)$ to $O(Q_F, q_F) + O(Q_W, q_W)$. The problem becomes as follows:

$$
\begin{align*}
\tilde{q}_f &= \arg\max_{q_f} \log \left( \frac{1}{N_s} \mathbf{I} + \frac{\rho}{N_0 \sigma^2} \mathbf{W}_{RF}^{\text{opt}} \mathbf{W}_{RF}^{\text{opt}} \Lambda + \mathbf{H}_{RF} \mathbf{F}_{BB} \mathbf{F}_{RF}^{\text{opt}} \mathbf{F}_{RF}^{\text{opt}} \mathbf{H}_{RF}^{\text{opt}} \Lambda \mathbf{W}_{RF}^{\text{opt}} \mathbf{W}_{RF}^{\text{opt}} \right), \\
\tilde{q}_w &= \arg\max_{q_w} \log \left( \frac{1}{N_s} \mathbf{I} + \frac{\rho}{N_0 \sigma^2} \mathbf{W}_{BB}^{\text{opt}} \mathbf{W}_{BB}^{\text{opt}} \Lambda + \mathbf{H}_{BB} \mathbf{W}_{BB}^{\text{opt}} \Lambda \mathbf{W}_{BB}^{\text{opt}} \mathbf{H}_{BB}^{\text{opt}} \Lambda \mathbf{W}_{BB}^{\text{opt}} \mathbf{W}_{BB}^{\text{opt}} \right),
\end{align*}
$$

subject to:

$$
\begin{align*}
q_f &= \arg\max \mathbf{H}_{RF} \mathbf{F}_{BB} \mathbf{F}_{RF}^{\text{opt}} \mathbf{F}_{RF}^{\text{opt}} \mathbf{H}_{RF}^{\text{opt}} \Lambda + \mathbf{W}_{RF}^{\text{opt}} \Lambda \mathbf{W}_{RF}^{\text{opt}} \mathbf{W}_{RF}^{\text{opt}} \mathbf{H}_{RF}^{\text{opt}} \Lambda + \mathbf{I} \\
q_w &= \arg\max \mathbf{H}_{BB} \mathbf{W}_{BB}^{\text{opt}} \Lambda \mathbf{W}_{BB}^{\text{opt}} \mathbf{H}_{BB}^{\text{opt}} \Lambda + \mathbf{W}_{BB}^{\text{opt}} \Lambda \mathbf{W}_{BB}^{\text{opt}} \mathbf{H}_{BB}^{\text{opt}} \Lambda + \mathbf{I}
\end{align*}
$$

After solving (9) and (10), the best analog precoder and combiner can be found from the feasible set $F_{RF}^{\text{opt}}, W_{RF}^{\text{opt}}, F_{BB}^{\text{opt}}, W_{BB}^{\text{opt}}$. At the same time, the baseband precoder and combiner can also be obtained accordingly. On this basis, the construction of network training data sets can be implemented.

### 4. Optimal hybrid beamforming coding based on CNN

The neural network architecture consists of two CNNs, which accept the input of the channel matrix and output the analog precoder and analog combiner weights respectively. In data generation, $N$ different channel matrices $H^{(n)}$ for different wireless network access node positions are generated together with the corresponding sets $F_{RF}^{(n)}$ and $W_{RF}^{(n)}$. For each channel implementation, these channel matrices will be destroyed by synthetic noise, and $L$ channel matrices containing noise are obtained, and the signal-to-noise ratio generated by the training data is defined as

$$
\text{SNR}_{\text{TRAIN}} = 20 \log_{10} \left( \frac{\mu_{\text{SNR}}}{\sigma_{\text{SNR}}} \right)
$$

The network input contains three channels. The first channel is the element-wise modulus of the channel matrix. The second and third channels include the real and imaginary parts of the channel matrix elements, respectively. Specifically, let $X$ be the network input matrix of size $N_R \times N_T \times 3$, and for the channel matrix $H$ of size $N_R \times N_T$, the first input channel is given by $|X|_{i,j} = |H|_{i,j}$. The second and third channels are given by $\text{Re}(|H|_{i,j})$ and $\text{Im}(|H|_{i,j})$ respectively. Therefore, the total size of the training input data is $N_R \times N_T \times 3 \times 3L$.

The convolutional neural network framework consists of two CNNs, each of which has 10 layers, and they have the same structure except for the last layer. The first layer is the input layer, which accepts channel matrix data with a size of $N_R \times N_T \times 3$, and for the channel matrix $H$, the first input channel is given by $|H|_{i,j}$. The second and fourth layers are convolutional layers, with 32 filters of size $3 \times 3$. After each convolutional layer, there is a normalization layer to normalize the output and provide better convergence. Sixth and eighth layers are fully connected layers with 1024 units. After the fully connected layers (the seventh and ninth layers), there are missing layers, and the loss rate is 50%. The output layer size of CNN $F$ is $N_T \times N_T^{\text{RF}} \times 1$, which includes the phase information of the analog precoder. The output layer size of similar CNN $W$ is $N_T \times N_T^{\text{RF}} \times 1$. The number of parameters can be calculated as:

$$
C^2 (2N_c(wh + 1) + 2(N_c + 1) \cdot \frac{50}{100})
$$

Where $C=3$ is the number of channels, $w=h=3$ is the filter size, $N_c=32$ is the number of filters, and $N_c=1024$ is the number of units with a 50% loss rate in the fully connected layer. Therefore, the convolutional neural network structure has $14995$ parameters.
The constructed convolutional neural network is trained and learned in the MATLAB simulation environment. A stochastic gradient descent algorithm with momentum of 0.9 is used, and the network parameters are updated with a minimum batch size of 0.005 for 100 time periods of learning and 500 samples. At the same time, cross entropy is used as the loss function. In the training, 70% and 30% of all generated data are selected as training and test data sets, and the verification data is used to test the performance of the network in the simulation of the Monte Carlo test\cite{14} with $J = 100$. Adding synthetic noise to the test data prevents similarities between the test data and the training data. The definition of signal-to-noise ratio during the test is similar to that of SNR$_{\text{TRAIN}}$,

$$\text{SNR}_{\text{TEST}} = 20 \log_{10} \left( \frac{L_{\beta} J}{\sigma_{\text{TEST}}} \right)$$  \hspace{1cm} (13)

5. Simulation result analysis

The number of analog precoders and analog combiners is set to $N_{RF} = N_{RF} = 4$. The constructed convolutional neural network provides training data generated by $N = L = 100$, and the azimuth and elevation angles are randomly selected from $\phi \in [-60^\circ, 60^\circ]$ and $\theta \in [-20^\circ, 20^\circ]$ respectively\cite{15}. This section provides simulation results in terms of achievable spectrum efficiency, energy efficiency, and UAV flight time to evaluate the performance of the proposed hybrid precoding scheme based on a phase shifter. The comparison methods include the proposed deep learning (DL) hybrid precoding method based on a phase shifter, the hybrid precoding method based on the manifold optimization algorithm (MO-AltMin), and the orthogonal matching pursuit algorithm (OMP hybrid precoding method, and full digital precoding scheme.

![Figure 2. Spectrum efficiency vs. SNR](image2)

![Figure 3. Energy efficiency vs. SNR](image3)

![Figure 4. Flight time under different battery capacities](image4)
Figure 2 analyzes the data stream $N_S=3$, $SNR_{\text{TEST}}=10\,\text{dB}$ and all hybrid precoding schemes use a phase shifter partial connection architecture, the system spectral efficiency comparison curve corresponding to different schemes under different signal-to-noise ratios. It can be seen from the figure that the performance of the proposed scheme is better than the MO-AltMin algorithm and the OMP algorithm under 1 bit phase resolution. It shows that the algorithm in this paper has better frequency performance under low resolution. Since the OMP algorithm is easy to fall into the local optimum, the best solution cannot be selected from the codebook, and the performance is poor.

Figure 3 analyzes the energy efficiency of different hybrid precoding schemes when the data stream is $N_S=3$ and $SNR_{\text{TEST}}=15\,\text{dB}$. Here, the MO-AltMin algorithm and the OMP algorithm are based on a high-precision phase shifter fully connected architecture, using a 4-bit phase shifter. This article uses actual values $\rho = 30\,\text{mW}$, $P_{\text{RF}} = 300\,\text{mW}$, $P_{\text{BB}} = 200\,\text{mW}$, $P_{4,\text{bit}} = 40\,\text{mW}$, $P_{1,\text{bit}} = 5\,\text{mW}$. It can be seen that the energy efficiency of the proposed scheme is the best among the several schemes compared, and the all-digital scheme with the highest spectral efficiency has the worst energy efficiency, because the radio frequency link unit consumes a lot of energy.

Figure 4 analyzes the UAV flight time under different hybrid precoding schemes. It can be seen that the proposed scheme will better increase the flight time of the drone compared with the all-digital precoding and the traditional scheme. This is because the low-precision phase shifter is used and the singular value decomposition and exhaustive search algorithm of the channel matrix are used.

6. Conclusions

In order to reduce the communication power consumption of inspection UAV, a energy efficiency hybrid precoding scheme based on one phase shifter is studied in its millimeter wave MIMO systems. UAV terminal uses a hybrid precoder and network access node uses a beam combiner. The joint estimation of the precoder and combiner is carried out through convolutional neural network. Simulation results show that this scheme has better energy efficiency and lower complexity than traditional algorithms, and effectively improves the flight time of the UAV.

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