Regression-Based Beam Training for UAV mmWave Communications

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Regression-based Beam Training for UAV mmWave Communications

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Abstract

For the unmanned aerial vehicle (UAV) Millimeter-Wave (mmWave) communication systems, an efficient and accurate beam training method is urgently required to overcome the severe path loss. By taking into account the mmWave propagation environment， a three-dimensional (3D) intelligent beam training strategy by leveraging the polynomial regression model and optimized beam patterns is proposed in this paper. We treat the mmWave beam selection as a polynomial regression problem. The regression function is obtained by a machine learning (ML) method based on the dataset and a special beam pattern is achieved to obtain the dataset consisting of measured powers and estimated angles. Furthermore, a noise suppression method involving the use of denoising autoencoder (DAE) is developed to improve the robustness of the proposed regression model. Numerical simulation results demonstrate that our proposed beam training strategy is capable of getting the same precision as the exhaustive search methods with a shorter time.

Keywords–UAV, mmWave communications, 3D beamforming ,3D beam training, machine learning.

1. INTRODUCTION

The commercial deployment of millimeter wave (mmWave) bands (27.5-28.35 GHz and 37-40 GHz) has made mmWave communication a promising technology for the fifth generation (5G) and beyond systems [1, 2]. With its large bandwidth and high transmission rate, mmWave has become the most feasible way to enhance UAV-assisted communication [3-6]. Due to the high spatial path loss the mmWave communication system usually utilize the large antenna arrays and beamforming (BF) technology to acquire high transmitting power gain [7]. However, the narrow beam and UAV's high mobility make the accurate beam pointing become a big challenge [8-13]. Therefore, a fast and precise angular search is necessary to get aligned beams between the receiver and transmitter during the initial access phase.

There have been a lot of works on the initial beam search. Exhaustive search algorithm was the best method in terms of accuracy, but the huge number of search time made it unacceptable for mmWave BF system[14-16]. In order to avoid brute force scanning and improve search efficiency, different solutions have been proposed. For example, the authors in [16] proposed a hierarchical multi-resolution codebook to lower the

training times. However, this method would introduce non-ideal probability of estimation error in some special angles. In [17], the authors developed two fast search procedures based upon Luus Jaakola and Tabu methods. In addition, various studies have looked at different beam search strategies in some specific scenarios. In [18], based on low-resolution phase shifters, the authors adopted hybrid analog-digital architectures to decrease power consumption, and used the greedy geometry algorithm to generate a hybrid beam to achieve performance similar to that of an all-digital beam. The authors in [19] proposed an efficient beam search scheme supported by the joint judgment. The authors in [20] presented an energy-efficient beam-alignment protocol to reduce power consumption. The authors in [21] gave a three-dimensional (3D) hierarchical codebook in order to estimate both the vertical angle and the horizontal angle at the same time.

For the beam search in mmWave UAV communication systems, it is difficult to get 3D aligned beam quickly without any additional information besides the measured power. Due to the increasing complexity of 3D BF systems, using machine learning (ML) or deep learning (DL) to improve beam search has become a promising method.

ML and DL have been utilized as effective tool to solve the regression and classification problems for a long time. In recent years, the application of ML/DL to BF field has received great attention. In [22], the authors used reinforcement learning to realize the beam selection based on a ray tracing simulator which generated mmWave channels with mobility of transceivers. The authors in [23] generated training data by using the ray tracing simulator and got the aligned beams on the basis of the vehicles position. These methods can only be applied to particular scenarios, once the scenario changes, it is necessary to rebuild the training model and recollect the training data. The authors in [24] and [25] investigated k-nearest neighbors (KNN) and support vector classifiers (SVC) to perform the selection of the optimal configuration for the analog beamforming (ABF) network based on the estimated angles-of-arrival (AOA) and received powers. In [26] and [27], the authors presented a Gaussian process based machine learning scheme to fulfill the fast and accurate UAV position prediction. These methods needed much prior message to calculate the probability distribution function of target variable. The aim of this work is to fill these gap. The major contributions and novelties of our work are listed as follows:

1）A fast 3D beam training strategy is designed in this paper. The novel strategy is implemented by using special frames with two-phase structure. The special functions and beams are presented in the corresponding phase.

2）A special linear regression model is proposed to replace the exhaustive beam search process and the ML algorithm is adopted to complete the fitting process. The proposed training model can simplify the search process and reduce the beam training time.

3) A novel beam pattern is designed based on the Fourier series method (FSM). The designed beam can help to increase the training efficiency, and promote the formation of linear regression model.

4) Based on the new training model, a denoising autoencoder (DAE) is proposed to increase the signal-to-noise ratio (SNR), which can improve the system performance in noisy environments.

The rest of this paper is organized as follows. In Section 2 describes the system model of UAV communications. Section 3, the fast 3D beam training model is introduced. Section 4 presents the DAE algorithm. Numerical results are provided in Section 5 and compares with the corresponding derivation results.

Finally, Section 6 concludes the paper.

For notations, Matrix and vector are denoted by $\mathbf{A}$ and $\boldsymbol{a}$,respectively. $\|\boldsymbol{a}\|_2$ is the Euclidean norm of $\boldsymbol{a}$, $\mathbf{A}^{\mathrm{T}}$ and $\mathbf{A}^{\mathrm{H}}$ are transpose and conjugate transpose of $\mathbf{A}$, respectively.

2. SYSTEM MODEL

The beam training is indispensable because of the narrow beams used in mmWave communications. UAVs need to get the aligned beams by beam training before establishing communication. When the communication is interrupted due to the drastic change of UAV's attitude and position, it is necessary to align beams again. In this scenario, uniform planar array (UPA) with the size of $M \times M$ is equipped in both the base station (BS) and mobile station (MS) . The channel model between the BS and MS, denoted by $\mathbf{H} \in \mathbb{C}^{M^2 \times M^2}$, can be expressed as

$$\mathbf{H} = q\boldsymbol{\alpha}_{MS}(\theta_h', \theta_v')\boldsymbol{\alpha}_{BS}^{\mathrm{H}}(\theta_h, \theta_v), \tag{1}$$

where q denotes the complex channel gain, θ_h and θ_v represent the horizontal and vertical beam direction of BS, respectively, θ'_h and θ'_v represent the horizontal and vertical beam direction of MS, respectively, $\boldsymbol{\alpha}_{BS}(\theta_h, \theta_v)$ and $\boldsymbol{\alpha}_{MS}(\theta_h', \theta_v')$ are the array responses of BS and MS, respectively. Furthermore, the array response of BS can be defined as

$$\boldsymbol{\alpha}_{BS}(\theta_h, \theta_v) = \boldsymbol{\alpha}_{BSh}(\theta_h) \otimes \boldsymbol{\alpha}_{BSv}(\theta_v), \tag{2}$$

where

$$\boldsymbol{\alpha}_{BSa}(\theta_a) = \left[1, e^{j\theta_a}, \cdots, e^{j(M-1)\theta_a}\right]^{\mathrm{T}}, \tag{3}$$

$$\theta_h = \frac{2\pi d_h}{\lambda} \sin\phi_h \cos\phi_v \tag{4}$$

and

$$\theta_v = \frac{2\pi d_v}{\lambda} \sin\phi_v. \tag{5}$$

Here $a \in \{h, \mathrm{v}\}$ includes both the horizontal and vertical domains, ϕ_a is the AOA, λ is the signal wavelength, d_h and d_v are the distance between adjacent antenna elements of horizontal and vertical direction, respectively, and $\boldsymbol{\alpha}_{MS}(\theta_h', \theta_v')$ can be formed in the same way.

The received signal can be modeled as

$$y = \sqrt{P}\boldsymbol{w}^{\mathrm{H}}\mathbf{H}\boldsymbol{c}r + \boldsymbol{w}^{\mathrm{H}}\boldsymbol{n}, \tag{6}$$

where P is the total transmit power, $\boldsymbol{w} \in \mathbb{C}^{MN \times 1}$ and $\boldsymbol{c} \in \mathbb{C}^{MN \times 1}$ are the combining and beamforming vector, respectively, r is the transmitted signal, $\boldsymbol{n} \in \mathbb{C}^{MN \times 1}$ is the complex white Gaussian noise with mean zero and variance σ^2.

3. METHODS SECTION :BEAM TRAINING

3.1 Training Strategy

The UAV beam training process can be regarded as a problem of angle selection. However, the main challenge is how to get the angles without knowing the positions and attitudes of the BS and MS. In this paper, we design a fast beam training strategy to overcome this problem. The strategy can be implemented by using the framework proposed in Fig. 1. It consists of the beam training phase and data transmission phase. In beam training phase, the BS transmits training sequences to the MS in each time slot. At the same time, the MS performs power measurements for beam configuration and feeds the results back to the BS. For simplicity, this paper assumes the channel between BS and MS is reciprocal. The beam patterns are shaped and the power measurements y_k are collected. The corresponding BF vectors for shaping beam pattern are obtained by the proposed method in section 3.2 and the beam directions can be achieved by $\theta = f(y)$. In the data transmission phase, the BS and MS utilize their beams, which obtained in the training phase, to transmit data.

As shown in Fig. 2, the traditional training strategy can be represented as a maximization function, and the output is the maximum power of the optimal beam pair. However, our method uses $\theta = f(y)$ to simplify the search process. The special beam pattern would be described in section 3.2, which can win the additional information beneficial to the training efficiency from the power measurements.

The regression model proposed in section 3.3 is the key point of novel training strategy to fit the function $\theta = f(y)$. As we known, the linear regression model is often adopted as its simplicity, therefore, we improve $\theta = f(y)$ to a linear regression function and the fitting process of function is completed by using ML algorithm in this paper.

For the traditional searching method, all beam patterns are same but the beam directions are different. The optimal beam pairs can be obtained by looking for the maximum power. Our strategy is using novel training beams by adding additional angle information, which can improve the efficiency and accuracy of beam training.

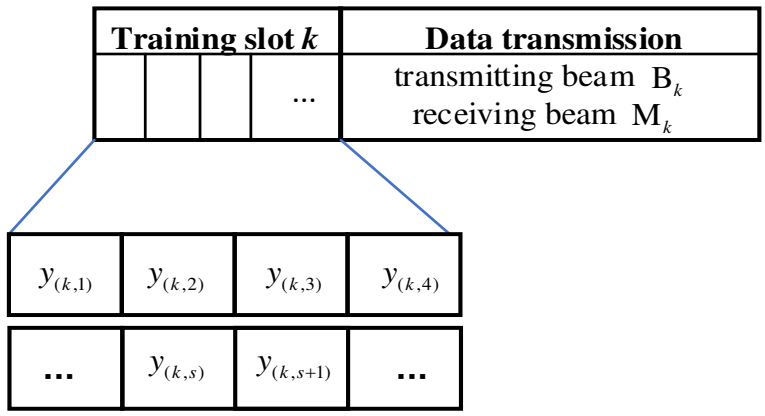

Fig.1 Conceptual framework

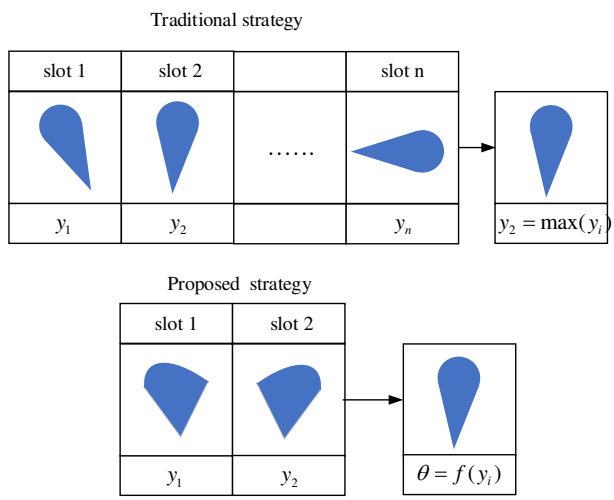

Fig.2 The traditional strategy VS proposed strategy

and the numerator is designed as a linear function of θ as

$$\begin{cases} |y_k|^2 - |y_{k+1}|^2 = z\theta + b \\ |y_k|^2 + |y_{k+1}|^2 = C \end{cases} \tag{8}$$

where Z and b are both constants. Furthermore, $|y_k|^2$ and $|y_{k+1}|^2$ are modeled as

$$\begin{cases} |y_k|^2 = \frac{1}{2} z\theta + b_1 \\ |y_{k+1}|^2 = -\frac{1}{2} z\theta + b_2 \end{cases} \tag{9}$$

where

$$\begin{cases} b_1 + b_2 = C \\ b_1 - b_2 = b \end{cases}. \tag{10}$$

It is difficult to design the BF vector which satisfy the beam patterns as (9). Therefore, we quantize the spatial domain into multiple regions. The beam gain of each quantified region is determined by the sample value of (9). For the convenience of explanation, an example is shown in Fig. 3. The relationship between horizontal direction and beam gain is also given. A similar approach can be followed to estimate the beam direction.

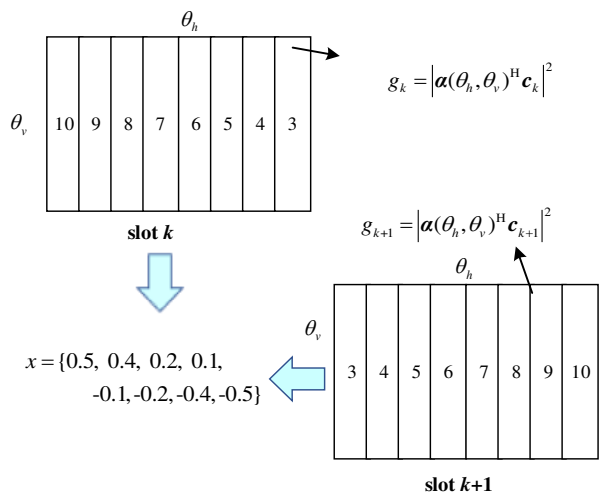

Fig.3 Ideal beam patterns for training data

Note that the numbers as 3,4,⋯⋯,10 in Fig. 3 only show a simplified distribution of beam gain. Using (7) to calculate x in all beam regions, we find that each θ_h of its corresponding region correlates to a specific x. Futhermore, x and θ_h are obey the monotonic relationship, which is a perfect relationship for fitting function $f(x)$ mentioned in this section utilizing ML.

The whole beam region in Fig. 3 is divided into several parts and the BF vector c for the i th region can be obtained by using the FSM [28]

$$\boldsymbol{c}_i(M \times (m_h - 1) + m_v) = e^{-j(X(m_h)\omega_{h0}(i) + Y(m_v)\omega_{v0}(i))} \cdot \frac{\sin(\omega_{h0}(i) X(m_h))}{\pi X(m_h)} \cdot \frac{\sin(\omega_{vb}(i) Y(m_v))}{\pi Y(m_v)}, \tag{11}$$

where (m_h, m_v) is the serial number of antennas, $X(m_h)$ is the ratio of antenna abscissa to horizontal separation d_h, $Y(m_v)$ is the ratio of antenna ordinate to vertical separation d_v, $(\omega_{h0}, \omega_{v0})$ is the center of beam region in horizontal and vertical domains, ω_{hb} and ω_{vb} are the width from center to horizontal and vertical boundary, respectively. The BF vector $\boldsymbol{c}_k$ is the sum of all $\boldsymbol{c}_i$ and defined as

$$\boldsymbol{c}_k = \sum \boldsymbol{c}_i. \tag{12}$$

Since the actual beam patterns generated by (12) cannot be exactly the same as Fig. 3, it only needs to ensure that the distribution of the beam gain meets the expectation. The relationship between input and output is not perfect linear. Therefore, ML is used to obtain an accurate regression model.

3.3 Polynomial regression Model

ML provides a variety of regression algorithms. Polynomial regression is a kind of linear regression model and has a wide range of applications, since any functions can be approximated by polynomial. Compared with the basic linear regression, it's suitable for nonlinear functions. In this paper, we utilize the polynomial regression to fit $f(x)$ and can be expressed as

$$f(\boldsymbol{x}) = \beta_0 + \beta_1 \boldsymbol{x} + \beta_2 \boldsymbol{x}^2 + \cdots + \beta_n \boldsymbol{x}^n, \tag{13}$$

where $\boldsymbol{x}$ and β_n are the feature and coefficient, respectively. The loss function of this model is

$$\mathrm{J}(\boldsymbol{\beta}) = \frac{1}{2}(\mathbf{X}\boldsymbol{\beta} - \mathbf{Y})^{\mathrm{T}}(\mathbf{X}\boldsymbol{\beta} - \mathbf{Y}), \tag{14}$$

where $\mathbf{X} = [1, \boldsymbol{x}, \boldsymbol{x}^2, \cdots, \boldsymbol{x}^n]$ and $\boldsymbol{\beta} = [\beta_0, \beta_1, \cdots, \beta_n]$. In this paper, power measurements are saved as $\boldsymbol{x}$ in the dataset. The beam direction θ is used as the training label for the regression. By minimizing the loss function, the coefficients β_n can be obtained.

The training result of ML method depends on both the learning model and the dataset. When the hand-crafted feature of (7) is applied, the search strategy is shown in algorithm 1.

Algorithm 1 Polynomial regression based on hand-crafted features

1	Generating A_1 and B_1; Collecting y_1
2	Generating A_2 and B_1; Collecting y_2
	Calculating $x_1 = \lvert y_1\rvert^2 - \lvert y_2\rvert^2 / \lvert y_1\rvert^2 + \lvert y_2\rvert^2$
3	Generating A_2 and B_2; Collecting y_3
	Calculating $x_2 = \lvert y_2\rvert^2 - \lvert y_3\rvert^2 / \lvert y_2\rvert^2 + \lvert y_3\rvert^2$
4	Generating A_3 and B_3; Collecting y_4
5	Generating A_4 and B_3; Collecting y_5
	Calculating $x_3 = \lvert y_4\rvert^2 - \lvert y_5\rvert^2 / \lvert y_4\rvert^2 + \lvert y_5\rvert^2$
6	Generating A_4 and B_4; Collecting y_6
	Calculating $x_4 = \lvert y_5\rvert^2 - \lvert y_6\rvert^2 / \lvert y_5\rvert^2 + \lvert y_6\rvert^2$
Output	$\theta_h = f(x_1)$, $\theta_v = f(x_3)$
	$\theta_h' = f(x_2)$, $\theta_v' = f(x_4)$

In the algorithm, A_1 and A_2 are the two beams of BS shown in Fig. 3. A_3 and A_4 are obtained by exchanging the parameters of θ_h and θ_v. The beam B of MS is obtained by the same way. According to the description in section 3.2, two measurements can determine one beam angle, θ_h or θ_v. For 3D beams, the four angles of beam pair can be obtained with eight measurements. As described in algorithm 1, the optimized searching strategy can get all beam angles only through six measurements, while the traditional one adopted hierarchical system can only complete the searching process of the first layer over the same time. Since the feature used by the algorithm 1 is one-dimensional variable, the polynomial regression of one indeterminate model is sufficient. In the initial stage, the function $f(x)$ is designed as an ideal linear function. Therefore, the estimated function curve is close to a straight line.

The features used in algorithm 1 are artificially designed. The error mainly comes from the difference between the actual beam and the ideal beam. Taking the estimation of the horizontal angle θ_h as an example, the ripples of the non-ideal beam in horizontal domain result in different horizontal angles with the same received power. In addition, the ripples in vertical domain result in different power values with the same horizontal angle. Note that the error affects the direction of aligned beam, but the main lobe can still cover the actual angle region.

The algorithm 1 can be used to verify the rationality of the presented beam design method. On this basis, the features can be replaced by the original power measurements. As shown in algorithm 2, four measurements are taken as characteristic variables, the horizontal angle and vertical angle are taken as labels. High-dimensional features can fit more complex data relationships. When the ripples of beam are very serious, our method can better learn the gain distribution of actual beams.

Algorithm 2 Polynomial regression based on original features

1	Generating A_1 and B_1; Collecting y_1
2	Generating A_2 and B_1; Collecting y_2
	$\vdots$
7	Generating A_4 and B_3; Collecting y_4
8	Generating A_4 and B_4; Collecting y_8
Output	$(\theta_h, \theta_v) = f(y_1, y_2, y_3, y_4)$,
	$(\theta_h', \theta_v') = f(y_5, y_6, y_7, y_8)$,

4. Noise Reduction

Since the inaccurate measurement cause by the noisy environment would lead to the incorrect estimation, a recurrent neural network (RNN) based DAE is proposed in this paper. Fig. 4 shows the framework of neural network.

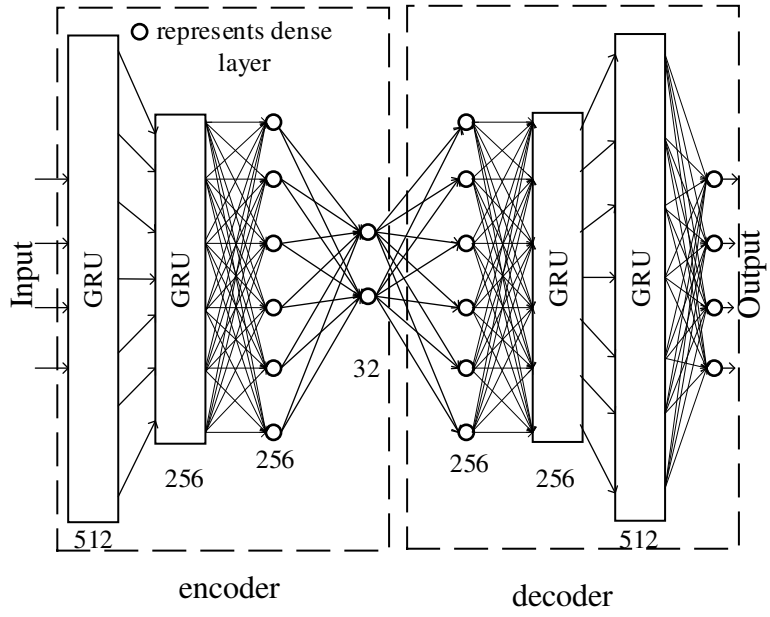

Fig.4 framework of the DAE

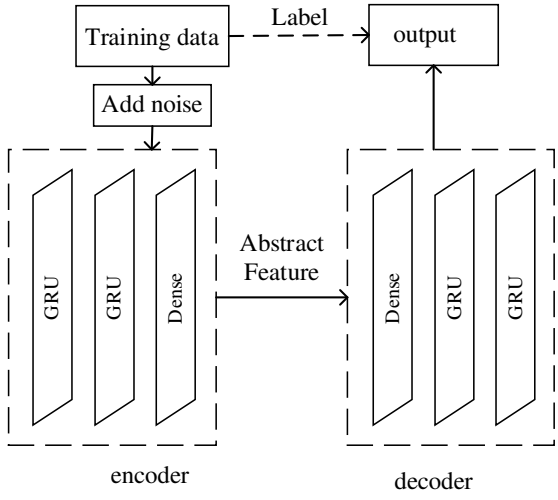

Fig.5 Process of the DAE

The DAE is composed of an encoder and a decoder. The encoder consists of one gated recurrent unit (GRU) layer with 512 units, one GRU layer with 256 units, one dense layer with 256 units, and one dense layer with 32 units. The structure of decoder is similar. Note that the simplest DAE comprises of only a number of dense layers. To better process the sequence data, we add GRU layers to the encoder and decoder.

In Fig. 5, the neural network establishes a mapping between the original data and noisy data. The original data is the beam direction values while UAV is working. We assume the noisy data is obtained by adding Gaussian noise to the original data. We first acquire the low dimensional feature by using the encoder to encode the noisy data, and then we restore the feature into the corresponding output data by utilizing the decoder. By employing the training data as labels, we can get a denoising learning model.

5. Discussion And Results Section

In this section, we provide numerical simulation results to verify the effectiveness of proposed beam training method. The beam pattern, regression model and DAE are the main factors that affect the performance of beam training. This paper mainly analyzes the efficiency of these main factors. The simulation parameters are as follows, $M = 21$, $q = 1$, $P = 30\text{dBm}$, and $d_h = d_v = \lambda/2$.

5.1 Beam Pattern

The beam pattern can promote the formation of linear regression model, and add additional information for the power measurement Therefore, the actual beam pattern should be close to the ideal one. Fig. 6 shows the actual beam formed by the presented BF method in section 3.2, where $\theta_a \in [-\pi/\sqrt{2}, \pi/\sqrt{2}]$. Fig. 6(a) shows that the designed beam pattern can satisfy the requirement of Fig. 3. It can be seen from Fig. 6 (b) and (c) that the beam gain changes with θ_h and is not influenced by θ_v. However, due to the limited number of array elements, there are many ripples in the beam pattern. Generally, the ripples can be reduced by adding windows, but it would increase the beam width and reduce the beam gain, which is more susceptible to noise interference. The ripples can also be reduced by increasing the number of array elements. Fig. 7 shows the beam pattern with different array elements. It can be found from the simulation results that the more array elements, the closer to the ideal beam.

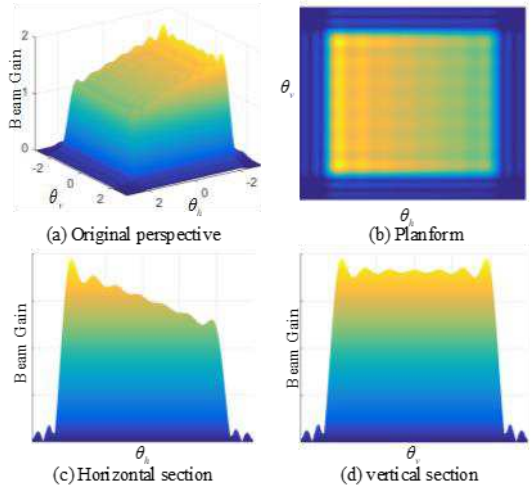

Fig.6 Beam patterns of proposed method

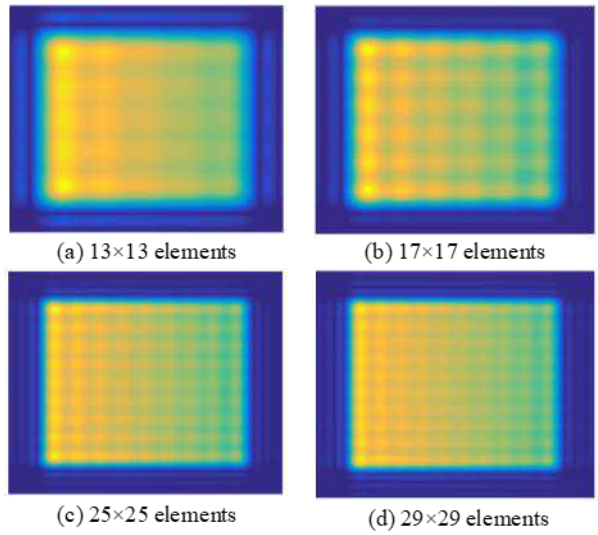

Fig.7 Beam patterns with different elements

5.2 Polynomial Regression

In this section, the attitude of UAV is simulated by changing the angle. The power measurements with different angles are collected as the input of training model. The actual angle is set as the label. To ensure the reliability of proposed model, the sampling angle values uniformly cover the entire beam width.

To verify the reliability of polynomial regression, the beam proposed in Fig. 6 is applied to algorithm 1. In this paper, we use the normalized mean squared error (MSE) to evaluate the accuracy of proposed model and analyze the influence of different parameters on the model. In Fig. 8, the value of degree represents the highest power of the polynomial in the polynomial regression model. The simulation results show that when the highest power of the polynomial is from 1 to 5, the MSE is relatively low. Form this result we can find that the function $f(x)$ can be well approximated to a linear model, and it is well consistent with the designing value of section 3.2. It is worth mentioning that the noise has a great impact on the performance.

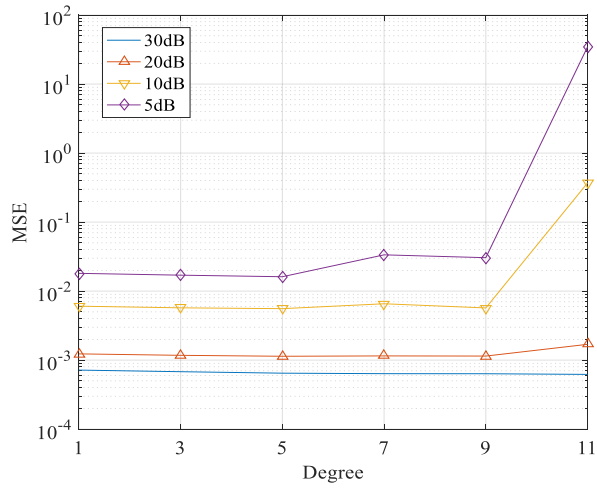

Fig.8 MSE of the polynomial regression

The fitting performance of different regression models is compared in Fig. 9. The curve of function $f(x)$ is also given. The dotted line is the actual curve, while the solid line is obtained by the polynomial regression model. It is worth noting that the designed beam pattern is adopted in the simulation. It proves that the designed beam is beneficial to promote the accurate fitting of regression model. However, the difference between the actual pattern and the ideal pattern may lead to different output with the same input, which would increase the training error.

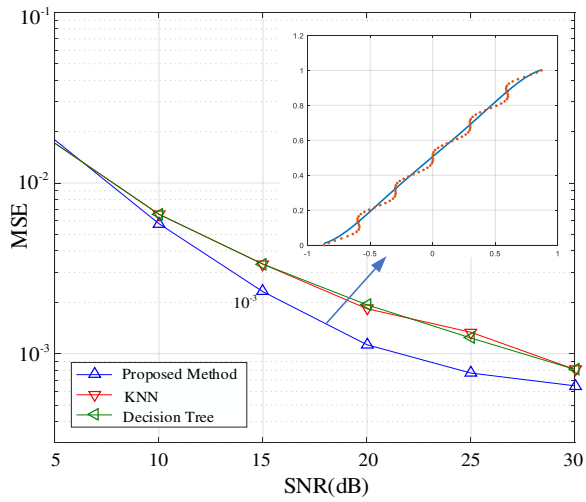

Fig.9 MSE of different regression models

By comparing three regression models, we can see that the polynomial regression model has the lowest MSE. It means that the polynomial regression can get reliable result when training the non-ideal dataset. KNN algorithm can deal with classification and regression problems simultaneously. The algorithm uses the mean value of several neighbor points as the predicted value of the model. The predicted value of decision tree depends on the mean value of sample points. Regression tree divides the feature space into several units, and each division unit has a specific output. For the test data, we need to group it into a unit according to its characteristics, and then search the corresponding output value. Both of two regression models can deal with the low-dimensional data, but they are not as effective as polynomial regression in dealing with the dataset as in this paper.

To verify the influence of original features on the regression model, we compare the MSE of algorithm 1 and algorithm 2 in Fig.10. As shown in Fig. 10, the regression method employing original features can effectively conduct angle estimation, and the estimation error is much smaller than the regression method using hand-crafted features. In addition, it can be found that the number of array elements has almost no effect on the estimation error. The reason is that the error of beam gain caused by the number of array elements does not affect the distribution characteristics of training data.

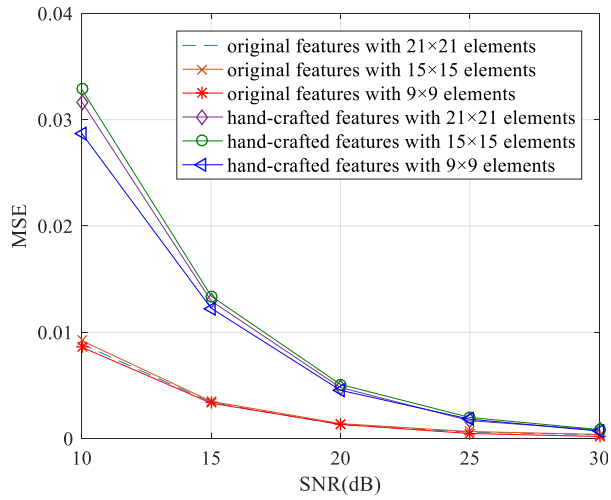

Fig.10 The influence of original and hand-crafted features

Due to the introduction of regression function and designed beam, only a small number of time slots are needed to complete the beam configurations. In our proposed training strategy, the reduction of training slots means the increasing of transmission time and data rate.

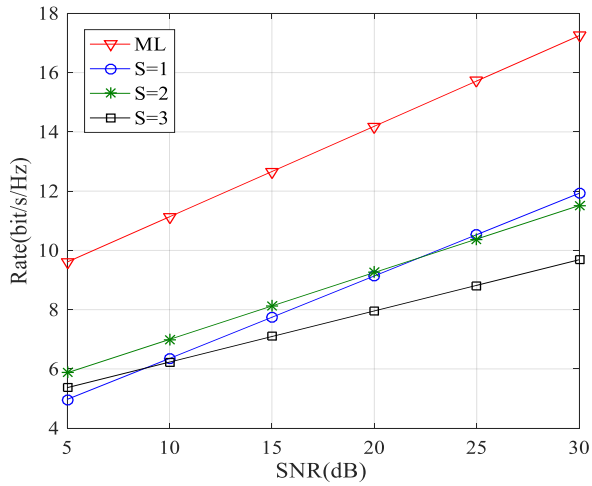

Fig.11 Data rate of different search methods

Fig. 11 shows the data rates of our method and hierarchical search when the beam configuration is finished. As shown in Fig. 11, in conventional method, if the hierarchical beam search only performs one layer training (S=1), the configuration time would be less. However, the data rate would be reduced as the beam gain of the first layer is too low. With the increasing of training layers (S=3), the beam gain increases. However, the time slots for data transmission would be reduced with the increasing of training time. By contrast, the training strategy proposed in this paper not only has a short training time, but also uses a narrow beam with high gain for data transmission. Therefore, the proposed method can provide the highest data rate.

5.3 DAE

In order to evaluate the effectiveness of the DAE model for noise reduction, we compared the normalized MSE of different algorithms under the same SNR. We take the noisy signal waveform as the input of DAE and the actual waveform as the training label. In order to prevent the neural network from over fitting, the input of training data should include a large number of waveforms with different amplitude and noise power.

Fig. 12 shows that the DAE could greatly reduce the error caused by the noise. Therefore, our proposed beam search algorithm could obtain aligned beams with less error. The MSE of exhaustive search represents the error between the maximum radiation direction of aligned beam and the actual direction. In order to obtain the minimum MSE of exhaustive search, we assume that there is no mismatch. We found that the proposed algorithm can achieve similar performance to exhaustive search, but the training time is much less.

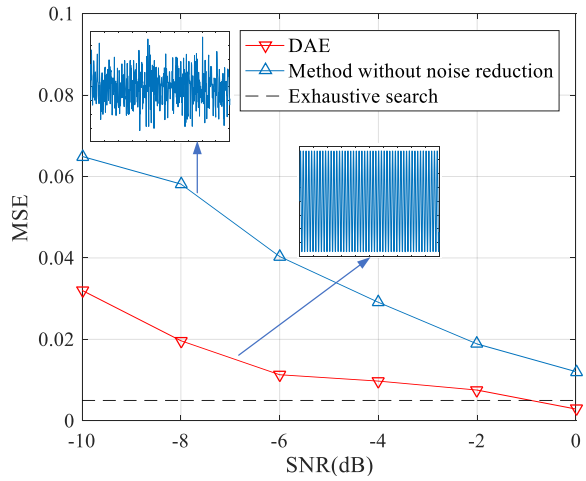

Fig.12 MSE of the DAE

6. Conclusion

In this paper, we presented a regression-based beam training method for UAV mmWave communication systems. Different with conventional multi-step training method, our proposed algorithm can improve the accuracy of training result while using less measurement data. The method utilizes the polynomial regression model of ML to fit the estimation function and designed the beam patterns to promote it. The simulation results has shown that the regression model can effectively complete the beam configurations on the basis of rational beam patterns design. In addition, the use of DAE can greatly reduce the MSE in noisy environments. In future work, we will employ the presented beam search algorithm on hardware platform and carry out field test in the realistic UAV flight scenes.

Abbreviations

UAV: Unmanned aerial vehicle; mmWave: Millimeter Wave; ML: Machine learning; DAE: denoising autoencoder; BF: Beamforming; DL: Deep learning; KNN: K-nearest neighbors; SVC: Support vector classifiers; AOA: Angles-of-arrival; FSM: Fourier series methods; SNR: Signal-to-noise ratio; UPA: Uniform planar array; BS: Base station; MS: Mobile station; GRU: Gated recurrent unit; MSE: Mean squared error;

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Author's contributions

ZJJ and ZWZ designed the algorithm and were the major contributor in writing the manuscript. GY and ZQM analyzed the data and the results of the algorithm. ZLL provided the communication scene. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

DECLARATIONS

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

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