Low Sweeping Overhead Method Based on Machine Learning in Beam Selection

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Abstract. Massive multi-antenna technology enhances spectral efficiency and system capacity in multi-user scenarios, thereby fulfilling the escalating demand for superior communication quality. This technology generates an increased number of spatial channels, referred to as independent beam pairs, to achieve higher spatial multiplexing. In such scenarios, users may select the optimal beam pair based on the conditions of their channels. The plethora of beams produced by a massive multi-antenna system presents a significant challenge in swiftly and efficiently selecting the optimal beam pair during initial connection setups. This paper proposes a method based on deep neural networks (DNN) that reduces the number of beam pairs needing consideration during the selection process, thereby minimizing overhead by searching for the optimal beam pair among a few recommended by the neural network.

Keywords: beam selection, machine learning, Beam management model, low overhead, Initial access

1 Introduction

In mmWave communication systems, beams at high frequency bands have more path loss, requiring beam management on both the downlink and uplink transmission and reception sides to find the best beam pair and ensure the quality of communication for the connection [1]. Large-scale antenna arrays provide more beams for mmWave communication, so an exhaustive search of all beams becomes computationally complex and increases the initial access time [2].

The literature [3] indicates that the optimal design choice for auxiliary beam selection during initial access depends on the specific deployment environment, considering factors such as base station density, antenna geometry, beamforming configuration, and integration with other technologies. Therefore, it is necessary to design the beam selection spatial model parameters reasonably when evaluating research performance. In recent years, some beam management algorithms have continuously optimized beam selection.

The literature [4] proposes a data-driven simulation beam selection method that analyzes historical data to predict the optimal beam configuration, thereby optimizing the performance of signal

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transmission. Sim et al. also simplified the beam selection process by predicting the optimal beam in the millimeter wave band from the channel information in the Sub-6 GHz band [5]. Faced with the complex problem of beam selection under high frequency and large number of array antennas in millimeter wave communication systems, Zhu et al. combined the Cuckoo Search (CS) algorithm with the Ant Colony Optimization (ACO) algorithm to improve the efficiency of beam selection [6]. However, when performing beam selection, the above studies did not consider directly optimizing the beams to be filtered, but focused on how to use optimization algorithms to reduce the time complexity in some beams.

To avoid repeated exhaustive searches and reduce communication overhead, this paper designs a machine learning model to assist in beam selection. It mainly considers the beam selection process when establishing an initial connection between the user equipment (UE) and the access network node (gNB). The external information possessed by the communication system in specific scenarios can be used as the input for machine learning [7]. The experiment uses the GPS coordinates of the receiver to assist in beam selection. To verify the robustness and scalability of the model, three beam selection models are mainly simulated as inputs for the neural network. Each model has one transmitter and the same number of receivers, but with different numbers of scatterers, which are randomly distributed in a certain space. The training samples consist of receiver locations (GPS data) and the optimal beam pair index found by exhaustive search of all beam pairs at the transmitter and receiver ends. The trained machine learning model will recommend K relatively good beam pairs for the receivers in the system. By performing a search only in the recommended K beam pairs, the beam with the highest average RSRP is selected. This method can reduce the beam sweeping time and selection overhead to a certain extent.

2 Basic configuration of beam selection system

2.1 Basic System Configuration

Firstly, the model has a cell ID for a single-cell scenario with a single base station (BS) and UE. In 5G NR, the frequency range is divided into two main parts: FR1 and FR2. The frequency band of FR1 is relatively low, so the propagation characteristics of the signal are good, with strong penetrating power, suitable for wide coverage scenarios, such as indoor and urban environments. This article chooses the FR1 frequency band and sets an appropriate center frequency. The subcarrier spacing of the synchronous signal block is 30 kHz, with a bandwidth of 25 MHz. The transmitter antenna array and receiver antenna array use a uniform rectangular array (URA). In order to perform a more comprehensive beam sweep in space, a certain range of azimuth and elevation angles in degrees is set to control the effective range of beam sweeping. The signal-to-noise ratio of the system is set to 20dB.

2.2 Layout of spatial model

In the beam selection model presented in this article, only the scenario involving one transmitter and multiple receivers is considered. To test the robustness of the neural network model, the transmitter, receivers, and scatterers are randomly distributed within a 1000 cubic meter space, with a total of 280 receivers. Three sets of simulations with varying numbers of scatterers are conducted, and the performance of the neural network is tested separately for each set.

2.3 RSRP calculation process

At the receiver end, to obtain reliable RSRP, the secondary synchronization signal (SSS) and the demodulation reference signal (DM-RS) in the physical broadcast channel (PBCH) are used simultaneously for measuring the synchronization signal block (SSB). In the 5G NR system, the RSRP can be used as a criterion for measuring the quality of a beam during the beam selection process [8].

2.3.1 RSRP measurement based on PBCH DM-RS

The measurement of RSRP usually relies on reference signals (RS), including PBCH DM-RS [9]. The specific steps include:

1. Detection of PBCH Demodulation Reference Signal: In 5G NR, PBCH DM-RS is usually transmitted on specific OFDM symbols. The receiver first needs to detect these symbols and lock onto the time and frequency resources of the PBCH DM-RS.

2. Extracting DM-RS symbols: Once the resources of the PBCH DM-RS are locked, the receiver can extract these symbols. The PBCH DM-RS is usually a QPSK modulated signal, which will be used for subsequent measurements.

3. Calculate RSRP: The RSRP can be calculated by extracting the DM-RS symbols. Specifically, let the amplitude of the DM-RS symbol be A_1, and the number of all resource units of PBCH DM-RS be N_1, then the RSRP can be obtained by the following formula:

$$RSRP = 10 \cdot \log \frac{A_1^2}{N_1} \tag{1}$$

2.3.2 RSRP measurement based on SSS

SSS and DM-RS provide different types of signal features. By utilizing both SSS and DM-RS simultaneously, a more stable signal reference can be provided, enhancing the robustness and reliability of measurements. SSS is mainly used for frequency and time synchronization, but it can also be used for RSRP measurements [10]. The main steps for measuring RSRP using SSS are: 1. SSS detection: The user equipment first completes time and frequency synchronization with the base station through the Primary Scratch Signal (PSS) and SSS. SSS is a component of the NR cell ID and is usually transmitted together with PSS and PBCH in the same SSB. 2. Extracting SSS symbols: After detecting the SSS, the user equipment needs to extract the frequency domain symbols where the SSS is located. The SSS is usually a BPSK modulated signal, so no complex demodulation process is required for extraction. 3. Power calculation: To measure RSRP, the user equipment calculates the received power of the SSS symbols. Assuming the amplitude of the SSS symbol is A_2, the number of SSS symbols is N_2, then the RSRP can be obtained by the following equation:

$$RSRP = 10 \cdot \log \frac{A_2^2}{N_2} \tag{2}$$

3 Experimental analysis

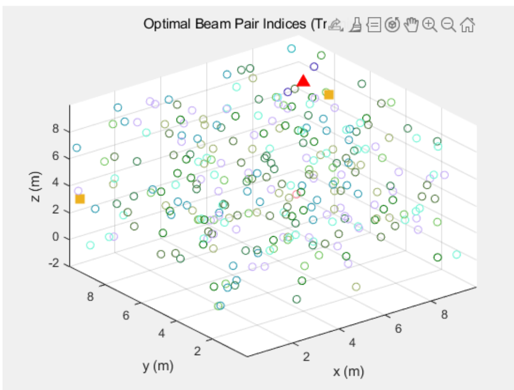
3.1 Beam selection process

To simulate the beam selection process in a NR cell, it is necessary to first generate NR synchronization signal bursts, perform beamforming on each SSB within the burst to sweep in azimuth and elevation angles, transmit this beamformed signal through a spatial scattering channel, and process this received signal on multiple receiver beams. Corresponding to the P-1 procedure defined in the 3GPP standard, bidirectional beam scanning is performed at the transmitter and receiver ends to determine the optimal beam pair for the link. During the beam scanning process, the transmitter emits synchronization signal blocks in multiple directions. Given the strong directionality and short transmission distance of millimeter waves, the receiver can determine the optimal beam pair by detecting the power and quality of these synchronization signal blocks, thus achieving precise beam alignment. To perform beam scanning using SSBs, this article configures appropriate SSB modes and the number of SSBs emitted. Since the transmitter and receiver are establishing a connection for the first time, the SSB period is set to 20ms.

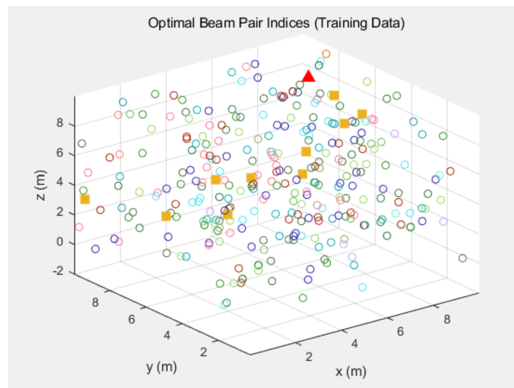
When the receiver performs beam scanning, it continuously receives the previously transmitted beamforming burst waveform on each receiving beam. The transmitter's antenna array consists of an 8x8 configuration, while the receiver's antenna array is a 2x2 configuration. In the P-1 procedure of the 3GPP standard, for N transmission beams and M receiving beams, each of the N beams is transmitted M times from the gNB to ensure that each transmitted beam is received on each of the M receiving beams. To align N and M with the number of SSBs in the burst, this document sets a total of 64 selectable beams, corresponding to the predefined number of SSBs in the system. To simplify this process, a single burst is generated, but the receiver processes this single burst M times to simulate the reception of M bursts over the air. Since the neural network needs to complete a classification task, the final output dimension is set to 64.

During beam scanning at the transmission end, the beam angles in the horizontal and vertical directions are first determined based on the number of SSBs and the scanning range. Then, each SSB undergoes beamforming using analog beamforming techniques. The beamformed SSB signals are then transmitted through the spatial scattering channel. Similarly, during beam scanning at the reception end, the beam angles in the horizontal and vertical directions are determined based on the number of SSBs and the scanning range. First, the received signals are applied to a spatially aware fading channel and receive gain is applied to compensate for path loss and AWGN. Then, beamforming is applied to the received signals, followed by time correction and OFDM demodulation. Through these processes, the known SSB grid can be extracted, and the RSRP is measured according to the specified measurement mode. Ultimately, the receiver marks the index of the beam pair with the highest average RSRP as the true optimal beam pair.

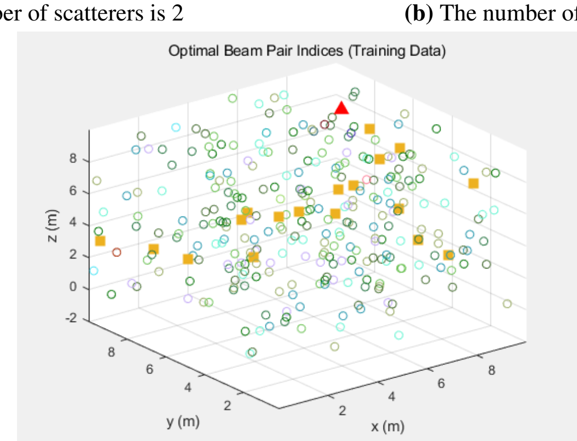
Since the positions of the transmitter, receiver, and scatterers are fixed within one round of random distribution rather than dynamically changing, certain beam pair indices may not be marked as the optimal beam pair. Fig. 1 illustrates the structure of a beam selection system with a random distribution corresponding to different numbers of scatterers. In Fig.1, red triangles represent transmitters, yellow rectangles represent scatterers, and circles represent transmitters. The 64 different colors used for the circles correspond to 64 beam pair indices, with the color of each circle representing its corresponding optimal beam pair index.



(a) The number of scatterers is 2



(b) The number of scatterers is 10



(c) The number of scatterers is 18

Fig. 1. Distribution of members in the beam selection system

3.2 Analog data processing

Due to the specific topological structure of the beam selection model, only a small number of or even no receivers select some of the 64 beams as their optimal beams. Fig. 2 shows the number of receivers corresponding to each beam in the training set in the generated input data when the number of scatterers is 10. Some beams are not selected or only a very small number of receivers select these beams. Such a distribution can cause certain problems. The neural network will see categories with a large number of samples more frequently, and thus tend to predict these majority classes more often, resulting in weak generalization ability and poor performance on new or unseen data.

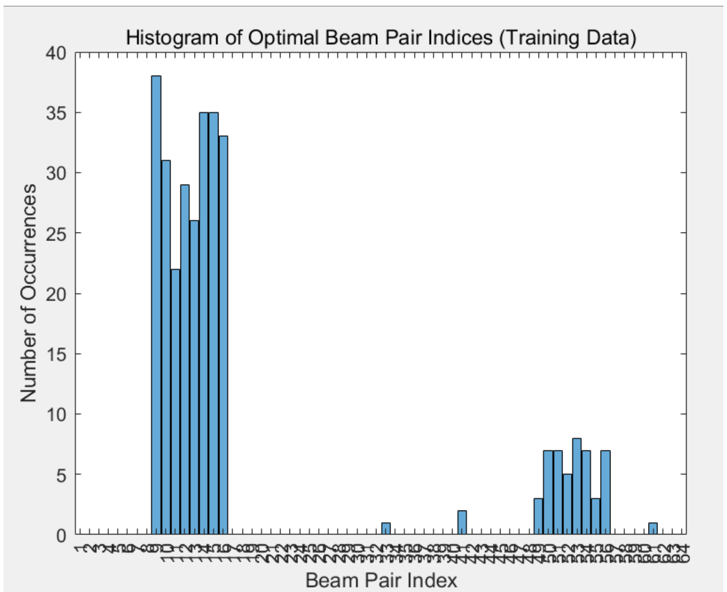


Fig. 2. When the number of scatterers is 10, the number of receivers corresponding to each beam pair index.

Therefore, a weight matrix needs to be designed to address this issue. Different weights are set for each category during calculation. For categories with a small number of samples, higher weights can be assigned proportionally, while for categories with a large number of samples, lower weights are assigned. Without changing the basic distribution trend of the samples, the characteristics of the input data in the first round are still retained. This effectively improves the adaptability of the model in facing various situations. By emphasizing the importance of these categories, the weight matrix helps the model find a more balanced learning path in the entire data distribution. The specific implementation method is to calculate the frequency based on the number of receivers corresponding to each beam. Because the number of receivers corresponding to some beams is 0, each beam is initially assigned a certain weight value, and for each category with a non-zero frequency, the weight is the ratio of the median frequency to the frequency of that category.

3.3 TOP-K Beam Selection in Neural Networks

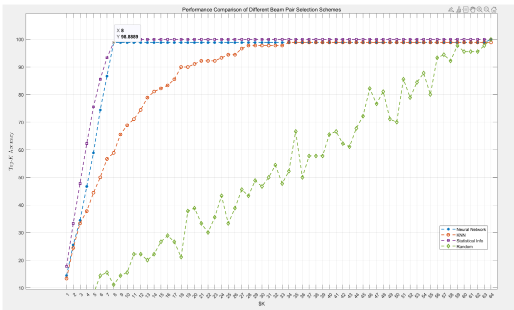
Using the beam selection system constructed above, a set of input data for neural network beam selection was obtained. The neural network is a 5-layer DNN, including three hidden layers. The neural network first outputs K recommended beam pairs. Then, an exhaustive search is conducted among these K beams, and the beam pair with the highest average RSRP is selected as the final prediction. If the true optimal beam pair is the one finally selected by the neural network, it indicates a successful prediction.

To illustrate the performance of the neural network designed in this paper, the results were compared with the best beam pairs found by KNN (K-Nearest Neighbors) and statistical information search methods. KNN is a basic and intuitive machine learning algorithm widely used in classification and regression tasks. The basic idea of KNN is to classify or regress by finding the labels or values of the K nearest neighbors of the sample to be predicted [11]. In the beam selection in this paper, KNN first collects K nearest training samples based on GPS coordinates. Then, the method recommends all beam pairs related to these K training samples. Since each training sample has a corresponding optimal beam pair, the maximum number of recommended beam pairs is K. The statistical information method ranks all beam pairs according to their relative frequency in the training set, and then always selects the top K beam pairs with the highest frequency, simply by selecting those with the highest probability to complete the task.

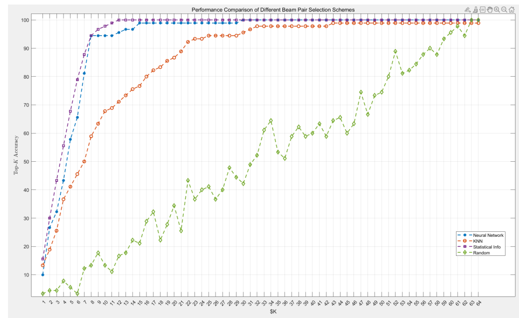
In the experiment, the Top-K accuracy, which is widely used in ranking tasks and recommendation systems, is adopted to evaluate the performance of the model [12]. Top-K accuracy mainly focuses on the accuracy of the model in the top K prediction results. Specifically, the number of correct answers included in the K predictions provided by the model determines the level of Top-K accuracy. This measurement method can effectively reflect the performance of the model in practical applications.

Fig. 3 shows the comparison of Top-K accuracy among the three methods, where the blue curve represents the neural network, the purple represents statistical information, the orange represents KNN, and the green represents random. The overall performance of the neural network is very close to statistical information. When the number of scatterers is 2, the neural network recommends 8 beam pairs, and the Top-K accuracy has reached 100%. In other words, the neural network saves unnecessary searching for another 56 beams for beam selection at this time, and only needs to choose from the 8 recommended beams to obtain the best beam pair. When the number of scatterers is 10 and 18, the neural network recommends 15 and 17 beam pairs respectively to achieve a Top-K accuracy of over 98%, indicating that in a more complex channel environment, the neural network can reduce more overhead for beam selection and ensure the reliability of the selection. When the number of training samples considered by KNN continues to increase and eventually approaches 64, the number of different beam pairs in these samples is usually less than 64, so the Top-K accuracy of KNN cannot reach 100%, which indicates that its reliability is lower than the neural network designed in this paper.

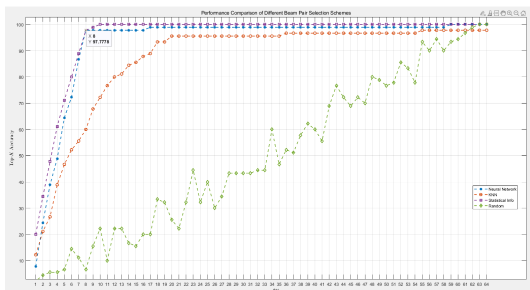
Fig. 4 illustrates the comparison of average RSRP under three scenarios. As the number of recommended beams increases, the blue curve representing the average RSRP value of the neural network can coincide with the red true value curve selected by exhaustive search from 64 beams. However, the orange curve representing KNN still shows a gap when the number of recommended beams approaches 64, and cannot ultimately reach the level of the true value.



(a) The number of scatterers is 2



(b) The number of scatterers is 10



(c) The number of scatterers is 18

Fig. 3. Comparison of average RSRP

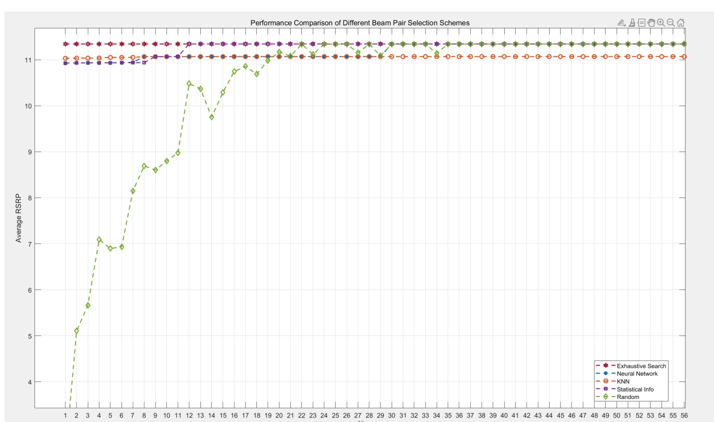


Fig. 4. Comparison of Average RSRP for Different Beam Selection Methods

4 Conclusion

Based on the GPS coordinates of the receiver, transmitter, and scatterer in a certain millimeter wave (MMW) communication system, a neural network can effectively screen out a set of beam pairs with optimal beams. By conducting exhaustive searches or using other algorithms within these beams, the overhead and time required for beam selection during initial access can be reduced to a certain extent. After testing with randomly distributed MMW communication systems of varying complexity, the neural network demonstrates robustness, adapting to different three-dimensional topological distributions and assisting in completing beam selection tasks. Additionally, it exhibits scalability, allowing for the integration of other predictive algorithms based on the neural network, focusing on the popular distribution locations of receivers within specific spaces, and pre-inputting these popular locations to enable the neural network to achieve screening and pairing more quickly.

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