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Predictive hierarchical beam training with noisy ranging measurements for mmWave vehicular communications

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***Abstract*—Beam alignment is not only a challenging but also an expensive task for massive multiple-input multiple-output (MIMO) enabled millimeter wave (mmWave) vehicular communications. In this paper, We propose a predictive hierarchical beam training strategy that only uses noisy-ranging measurements. The position and also angular deviation are first predicted based on the noisy ranging measurements. Then the initial searching layer and also the corresponding codewords are derived from the predicted position, the angular deviation of vehicular user equipment (VUE), as well as the ranging error. Simulation results show that even with dynamic scatters and imperfect knowledge of the VUE locations, the proposed strategy can reliably find the optimal beam with greatly reduced training time.**

***Index Terms*—Millimeter-wave communications, Massive MIMO, hierarchical beam training, noisy ranging measurement**

I. Introduction

Millimeter-wave (mmWave) communication can meet the extremely high data rate requirements of networked vehicles [1], [2], owning to the abundant spectrum resources. However, the propagation of mmWave signal is susceptible to obstructions. Therefore, the beamforming gain provided by massive multiple-input multiple-output (MIMO) is usually exploited to compensate for the serious propagation loss [3]. The following problem is the beam training, *i.e.*, finding the best transmitting/receiving beam pair between the transmitter and receiver, which is a time-consuming task, especially considering the high mobility of vehicular user equipment (VUE).

Exhaustive beam training is the most intuitive method to find the best beam pair, which would cause unaffordable overheads and is thus inefficient for vehicular communications [4]. In this regarding, hierarchical codebooks are designed to support hierarchical beam training to reduce overheads [5]. Hierarchical codebook includes several layers with different beamwidth, where the spatial area covered by the codeword at the upper layer is divided into several smaller spatial areas covered by several codewords at the lower layer [6]. This kind of hierarchical beam training has also been widely used in commercial mmWave communication systems, such as IEEE 802.11ad [7].

The further enhancement for hierarchical beam training has also attracted considerable attention. For example, the Bayesian tree search algorithm based on statistical detection theory is utilized in [8] and [9] to decrease the search delay of hierarchical beam training. However, the resulted power gain at the edge of the beam may be lower than that at the center of the beam, which makes it prone to wrong codeword selection in the coarse codebook search. In [10], the antenna deactivation processing is adopted to restrict the beamwidth of hierarchical codebooks, which can only be achieved by analog beamforming structure. In [11], a beam pattern shaping approach (BPSA) is proposed, which formulates the codebook design to an optimization problem, where the main/sidelobe ripple is limited so that each training beam is similar to the ideal beam, with a narrow transition zone and flat amplitude response. However, the methods discussed above are still hard to meet the extremely low overhead requirement in the high mobility scenario.

In recent years, predictive and out-of-band information aided beam training are emerging methods to further reduce the overhead and delay [12]. To be more specific, in [13], the low-frequency interface of multi-band equipment is used to forecast relative angle information when the link is in a connected state, which also enable communication fallback in the case of mmWave link interruption. In [14], the sensors (gyroscopes, accelerometers, and magnetometers) are adopted to determine the rotation and movement of vehicles. However, in order to keep overall overhead and delay down, the position information should be obtained through in-band and does not rely on out-of-band data, especially in the dense mmWave networks. Hence, it is desirable to derive the position only from the network measurements in the physical (PHY) and medium access control (MAC) layers. Hence, in this paper, a predictive hierarchical beam training method that only uses noisy ranging measurements is proposed for mmWave vehicular communications.

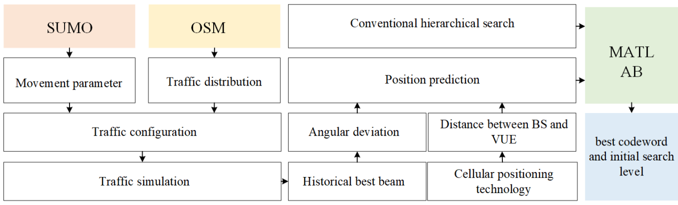

Fig. 1. The flowchart of predictive hierarchical beam training

The method proposed in this paper includes three stages: position prediction based on noisy measurements, initial searching layer prediction, and dynamic codeword selection. The flow chart of the overall method is shown in Fig. 1: On the one hand, by setting the movement parameters of Simulation of Urban Mobility (SUMO) and obtaining the traffic distribution of Open Street Map (OSM), the traffic configuration in the actual scene is obtained, and then the traffic simulation is performed to obtain the historical best beam and further obtain the angular deviation. On the other hand, cellular positioning technology is used to obtain the distance between the BS and the VUE. Predict the position according to the angular deviation and distance obtained above, combine it with the traditional hierarchical search method, and use the matrix laboratory (MATLAB) for simulation to obtain the best initial search level of prediction and the best prediction codeword.

The notations are as following. Symbols for vectors (lower case) and matrices (upper case) are in boldface. $[a]_n$ means the nth entry of a vector $\boldsymbol{a}$. $()^*$denotes the conjugate, $()^T$ denotes the transpose, $()^H$denotes the conjugate transpose (Hermitian), $||$ denotes absolute value, $||||_2$ denotes l_2- norm, $\mathbb{C}$ denotes set of complex number, $\mathbb{Z}$ denotes set of integer number, E represents operation of expectation, $\backslash\backslash$ represents operation of set exclusion and $\mathcal{CN}$ represents complex Gaussian distribution.

II. System Model

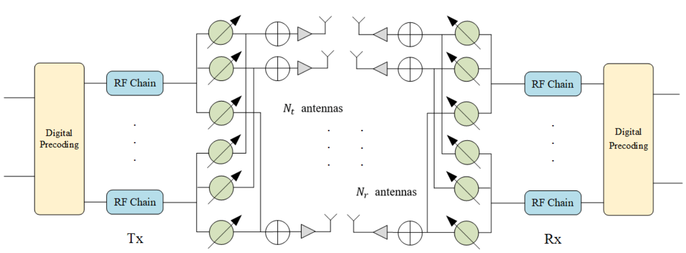

Fig. 2. Hybrid beamforming transceiver architecture

Without loss of generality, we consider a point-to-point, single-user mmWave MIMO system, as shown in Fig. 2. We assume both BS and VUE are equipped with a uniform linear array (ULA) with half-wavelength antenna spacing, containing N_t and N_r antennas, respectively. For ease of analysis, assuming that both N_t and N_r are powers of two. The training symbol x is transmitted during beamforming, which has standardized power, i.e. E$\{xx^*\}$=1, The received signal is then expressed as:

$$y = \sqrt{P}\boldsymbol{w}_{BB}^H\boldsymbol{W}_{RF}^H\boldsymbol{H}\boldsymbol{F}_{RF}\boldsymbol{f}_{BB}x + \boldsymbol{w}_{BB}^H\boldsymbol{W}_{RF}^H\boldsymbol{\eta}, \quad (1)$$

where $\boldsymbol{f}_{BB} \in C^{N_{RF}}$ denotes the digital precoder, $\boldsymbol{F}_{RF} \in C^{N_t \times N_{RF}}$ denotes the analog precoder, $\boldsymbol{w}_{BB} \in C^{N_{RF}}$ denotes the digital combiner, $\boldsymbol{W}_{RF} \in C^{N_t \times N_{RF}}$ denotes the analog combiner, $\boldsymbol{H} \in C^{N_r \times N_t}$ denotes the mmWave massive MIMO channel, $\boldsymbol{\eta} \in C^{N_r}$ denotes the additive white Gaussian noise (AWGN) vector and $\boldsymbol{\eta} \sim CN(0, \sigma_\eta^2)$. P is the total transmitted signal power. Note that in this article, we assume that neither the precoder nor the combiner provides power gain, which is consistent with common assumptions. The mmWave MIMO channel matrix is expressed as following:

$$y = \sqrt{N_t N_r / L}\sum_{l=1}^{L}\lambda_l \boldsymbol{\alpha}(N_r, \Omega_l^r)\boldsymbol{\alpha}(N_t, \Omega_l^t)^H, \quad (2)$$

where L denotes the number of multi-path components, λ_l denotes the channel gain, Ω_l^r denotes angle-of-arrival (AoA) of the channel of the lth path, and Ω_l^t denotes angle-of-departure (AoD) of the channel of the lth path. The physical AOD and AOA of the lth path are defined as ω_l^t and ω_l^r,respectively. Due to $\omega_l^t \in [0, 2\pi)$ and $\omega_l^r \in [0, 2\pi)$, For the half-wavelength interval between adjacent antennas, let $\Omega_l^t = cos(\omega_l^t)$ and $\Omega_l^r = cos(\omega_l^r)$. As a result, both $\Omega_l^t \in [-1, 1]$ and $\Omega_l^r \in [-1, 1]$. Define the channel steering vector as a function of N and Ω, which is

$$\boldsymbol{\alpha}(N, \Omega) = 1/\sqrt{N}[1, e^{j\pi\Omega}, ..., e^{j(N-1)\pi\Omega}]^T, \quad (3)$$

Where N is the number of antennas, Ω is the channel AOA or AOD.

A. Hierarchical Codebook Design

The focus of hierarchical beam training is to effectively search the dominant path. Hierarchical codebooks consist of codewords with different beamwidth, which helps to search efficiently and find the steering vector of the strong or strongest MPC on either side [15]. When beamforming is required before data transmission, a beamforming process needs to be carried out according to the designed codebook to find the appropriate beamforming vector for a given channel.

Hierarchical search is to layer the antenna weighted vector (AWV) in the codebook according to its beamwidth, and the AWV in the lower layer has a wider beam. The design of hierarchical codebooks follows two basic principles. Let $\boldsymbol{w}(k, n)$ represent the nth codeword (or AWV) of the k layer, and the two criteria are as following: $\mathbf{Criterion1}$: The sum of the beam range of all codewords in each layer should cover the whole angle domain, i.e

$$\bigcup_{n=1}^{N_K} \mathcal{CV}(\boldsymbol{w}(k, n)) = [-1, 1], k = 0, 1, ..., K, \quad (4)$$

where N_k is the number of codewords at layer k, and K is the maximum index of this layer (total layer K+1). $\mathbf{Criterion2}$: The beam range of any codeword in one layer should be

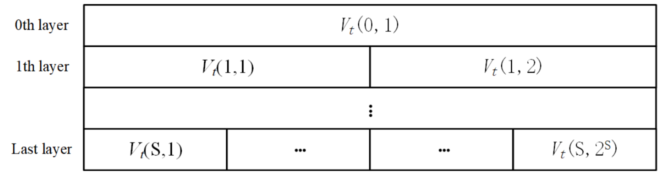

Fig. 3. Beam range of binary tree structure codebook

covered by the sum of the beam range of multiple codewords in the next layer, i.e

$$\mathcal{CV}(\boldsymbol{w}(k,n)) \subseteq \bigcup_{m\in\mathcal{I}_{k,n}} \mathcal{CV}(\boldsymbol{w}(k+1,m)), k=0,1,...,K-1, \tag{5}$$

where $\mathcal{I}_{k,n}$ is the index set of the $(k+1)$ level of the nth codeword at the k level. For simplicity, we regard $\boldsymbol{w}(k,n)$ as parent codeword, and $\boldsymbol{w}(k+1,m)|m\in\mathcal{I}_{k,n}$ as the child codewords of $\boldsymbol{w}(k,n)$.

Hierarchical search scans from top to bottom using specific codeword of each layer to find the best-received codeword according to the codebook. In each layer, there are a total of M candidate codewords, which are M sub-codewords of the parent codewords filtered in the last stage. We need to train all M codewords in turn and find the best one to use as the new parent for the next stage of the beam search. Therefore, the search time of TX/RX joint training is:

$$T = Mlog_M(N_t) + Mlog_M(N_r). \tag{6}$$

Generally, the number of antennas used in antenna array design is a power of 2. Therefore, the number of existing hierarchical codewords is $M = 2$, as shown in Fig. 3. In addition, it is very simple to extend the proposed method to other values of M. Since the hierarchical codebook principle and design method of the receiver and transmitter are the same, we mainly concentrate on the design of the transmitter codebook V_t. Express the $i (i = 1,2,...,N_t)$-th codeword of the bottom layer of the binary codebook V_t as:

$$\boldsymbol{f}_i = \boldsymbol{\alpha}(N_t, -1 + (2i-1)/N_t), \tag{7}$$

which is actually a channel direction vector with beam range of $[-1+2(i-1)/N_t, -1+2i/N_t]$. In order to design a normalized codeword $\boldsymbol{v} = \boldsymbol{V}_t(s,m)$, the union of the subscript sets of $\boldsymbol{f}_i$ can be described as:

$$\Psi_{s,m} = \left\{ i | \frac{(m-1)N_t}{2^s} + 1 \le i \le \frac{mN_t}{2^s} \right\}. \tag{8}$$

Then we can calculate a general codeword as the weighted sum of the channel steering vector:

$$\hat{\boldsymbol{v}} = \sum_{i\in\Psi_{s,m}} e^{j\theta_i}\boldsymbol{f}_i, \tag{9}$$

where θ_i is used to eliminate the low beam gain within the range where the beam covers [16], according to [17], θ_i can be set as:

$$\theta_i = i\pi(-1 + \frac{1}{N_t}). \tag{10}$$

In order to fairly compare different codewords in each test, we normalize $\hat{\boldsymbol{v}}$, that is:

$$v = \frac{\hat{\boldsymbol{v}}}{\|\hat{\boldsymbol{v}}\|_2}. \tag{11}$$

According to (6), it can be seen that the complexity is still high. At the beginning of the search, the beam width is wider and the beamforming gain is lower, misalignment is prone to occur. Therefore, it is necessary to design a more efficient hierarchical search that increases the initial search level to reduce the complexity and misalignment.

III. Predictive Hierarchical Beam-tracking Method

A. Position prediction based on noisy angular measurements

The current cellular network native supports positioning functions, such as the continuously enhanced RTT [18], where the distance between the VUE and the base station can be estimated through time advance (TA) to get the signal from VUE to the base station, or the time from the base station to VUE, multiplied by the speed of light (wireless signal propagation speed), and the measurement accuracy can be up to 5 meters. Although RTT has obtained good results, there still are problems including the received signal strength which is highly affected by the position. Therefore, this paper proposes a location prediction method based on noisy ranging measurements. As shown in Fig. 4, the goal of this stage is to get and initialize the following historical data:

- Position obtained through cellular positioning technology. The two-way arrival time is adopted to estimate the transmission distance. The expression of BS-VUE distance is:

$$\tilde{r} = r + e, \tag{12}$$

  where r is the actual BS-VUE distance depending on RTT and TA measurement accuracy and e is a normally distributed random variable with a mean of zero and a standard deviation of σ_e.
- The best beam to use in the first four positions is called the geometry-based prediction method. To reduce the cost of the pilot to an affordable level, based on the historical data, the optimal beam of four positions is obtained, and the corresponding AoA /AoD is derived. By defining the two-dimensional cartesian coordinate system and placing BS at (0,0), the position of VUE can be estimated as:

$$p(x,y) = (\tilde{r}cos\tilde{\theta}, \tilde{r}sin\tilde{\theta}), \tag{13}$$

  where $\tilde{\theta}$ is the main lobe direction of the optimal beam, representing the estimated direction of VUE, and x and y are horizontal and vertical coordinates respectively. In the case of short intervals, RTT is typically at the millisecond level, therefore, we consider $T = 1s$ for convenience, each segment can be modeled as moving in a uniform straight line:

$$v_i = |p(t-3+i) - p(t-4+i)|/T, \tag{14}$$

where v_i refers to the velocity of the vehicle, T denotes the period measurement. In the case of a short interval (e.g. $T = 1s$), it is assumed that each velocity change is a uniform acceleration linear motion:

$$a_i = (v_{i+1} - v_i)/T. \tag{15}$$

It is assumed that every change in acceleration is a uniform acceleration motion, then the corresponding acceleration at next time is:

$$a_3 = \frac{a_1 + a_2}{2}. \tag{16}$$

Therefore, the velocity of VUE in $[t, t+1]$ is:

$$v_4 = v_3 + a_3 T = |p(t+1) - p(t)|/T. \tag{17}$$

It is assumed the angle between the line of $p(t-2)$ and $p(t-3)$ and the horizontal axis is θ_1, and so on, $p(t-1)$ and $p(t-2)$ are connected to the horizontal axis at an angle θ_2, the angle of the connection between $p(t)$ and $p(t-1)$ and the horizontal axis is θ_3, then the included angle of the connection between $p(t+1)$ and $p(t)$ and the horizontal axis is:

$$\theta_4 = \frac{\theta_1 + \theta_2 + \theta_3}{3}. \tag{18}$$

Thus, it can be concluded that:

$$p(t+1) = p(|p(t+1) - p(t)|cos\theta_4, |p(t+1) - p(t)|sin\theta_4), \tag{19}$$

where t denotes the current moment.

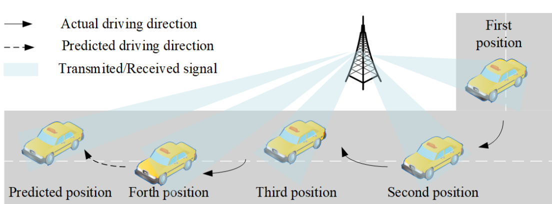

Fig. 4. Schematic diagram of millimeter wave vehicle networking

B. Initial searching layer prediction

In the previous section, the potential beam direction was predicted based on the trajectory of the vehicle. It will be proved in the subsequent simulation result. In this section, for the BS to determine the coverage in which the VUE is located, initial layer prediction is adopted. According to our proposed position prediction algorithm, different distance variances will lead to different predicted positions, which will result in different angle deviation predictions such as AoD/AoA. Then, according to the predicted positions and angular deviation, the initial search level of the corresponding hierarchical codebook at the next moment can be predicted. The specific process is shown in Algorithm 1.

At first, the serial number of the leftmost codeword v_l is 1, while the serial number of the rightmost codeword v_r is 256. And the initial search level s is 1.

$$s = v_r - v_l + 1, \tag{20}$$

where s refers to the search range of the codeword corresponding to the nth layer.

Algorithm 1 Predict the initial search level and codeword

Require: v_l, v_r, s
Ensure: s, $\boldsymbol{w}_{s,m}$

while $v_l + 1 < v_r$ **do**
  Obtain v_{left} from (21)
  Obtain v_{right} from (22)
  if $v_l < v_{left}$ and $v_{right} < v_r$ **then**
    $break$
  end if
  $s \leftarrow s + 1$
  if $v_l > v_{left}$ **then**
    $v_l \leftarrow v_{right}$
  else
    $v_r \leftarrow v_{left}$
  end if
end while
Obtain $\boldsymbol{w}_{s,m}$ from (23)
return s,

$$v_{left} = (v_r + v_l - 1)/2, \tag{21}$$

where $[v_l, v_{left}]$ is the search interval to the left of the codeword.

$$v_{right} = (v_r + v_l + 1)/2, \tag{22}$$

where $[v_{right}, v_r]$ is the search interval to the right of the codeword.

$$\boldsymbol{w}_{s,m} = (v_l - 1)/(256/2^s), \tag{23}$$

where $\boldsymbol{w}_{s,m}$ is the initial codeword at each search level.

C. Dynamic codeword selection

Algorithm 2 hierarchical beam tracking based on noisy ranging measurements

Input: s, $\boldsymbol{w}_{s,m}$, $\boldsymbol{w}_{s,m+1}$,
Output: $\boldsymbol{w}^*_{s,m}$

for $s = l \to S$ **do**
  Obtain $y_{s,0}$ from (1)
  Obtain $y_{s,1}$ from (1)
  if $y_{s,0} < y_{s,1}$ **then**
    $m := 2m$
  end if
end for

In our proposed method, the angular error is obtained according to the driving trajectory of the vehicle flexibly, and the codeword set of the initial layer is constructed according to the angular error. The basis for judging the best beam is as follows:

$$\underset{\boldsymbol{v}_k, \boldsymbol{w}_k}{max} |\boldsymbol{w}_k^H \boldsymbol{H} \boldsymbol{v}_k|, \tag{24}$$

where $\boldsymbol{v}_k$ and $\boldsymbol{w}_k$ are codewords of codebook $\boldsymbol{V}_t$ and $\boldsymbol{V}_r$, respectively. The specific process is shown in Algorithm 2.

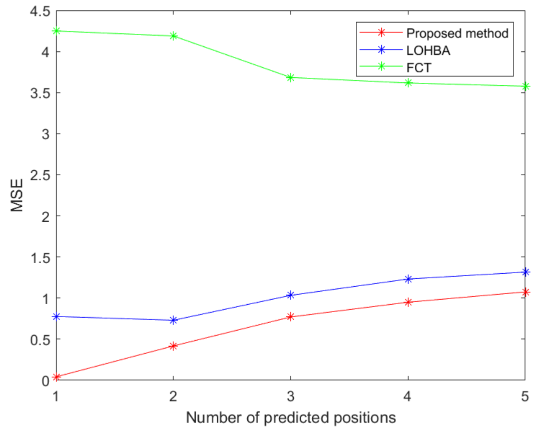

Fig. 5. MSE for different prediction position number under FCT, LOHBA and the proposed method

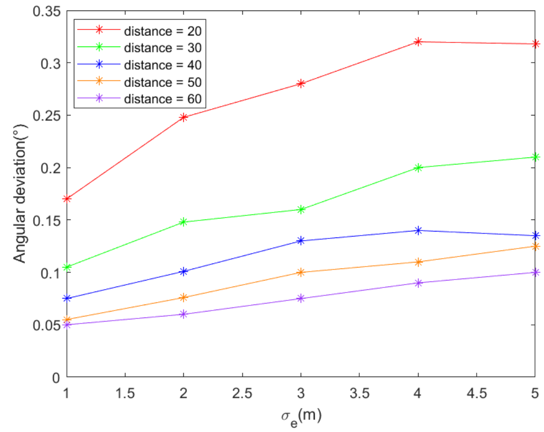

Fig. 6. Angular deviation for different distance deviation value under different distance between BS and VUE

Transmitter sends pilot signals beamformed by $\boldsymbol{w}_{s,m}$ and $\boldsymbol{w}_{s,m+1}$. And the receiver obtains corresponding signals $y_{s,0}$ and $y_{s,1}$, comparing them according to (24). Finally, the best received codeword $\boldsymbol{w}^*_{s,m}$ is obtained.

IV. Simulation Results and Analysis

In this paper, the proposed method employs the single-level codebook, with $N_t = 256$ ideal transmitter beams covering AoD range [0, 2π] and $N_r = 256$ ideal receiver beams covering AoA range [0, 2π]. The total number of search levels of the hierarchical search is $S = 8$. The distance between two adjacent antennas is $d = \lambda/2$. Besides, Channel gain λ_l obeying $\mathcal{CN}$ $(0, 1)$. We assume that AoA and AoD are uniformly distributed in the interval $[-\pi, \pi]$. The number of predicted positions steps can be $1, 2$ or 3; If some larger values are taken, the accuracy of the position prediction method will be lower. The variance of the distance error σ_e is in the range $[0, 5]$. Without loss of generality, only the line-of-sight path is considered, so L is 1. We also enforce that the transmit signal maintain unit power: E$\{xx^*\}$=1. The effectiveness of the proposed approach is evaluated by MSE:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\tilde{\theta} - \theta)^2. \tag{25}$$

Fig. 5 compares the relationship between the accuracy of location prediction of different methods as the prediction step increases. It is seen the MSE of the fast channel tracking (FCT) location prediction algorithm is much larger than the proposed method and low-overhead hierarchical beam-tracking algorithm (LOHBA). As the number of location prediction steps increases, the MSE of the proposed location prediction method and another location prediction method gradually become larger. Note that the MSE of our proposed method is always smaller than the MSE of the FCT location prediction algorithm and slightly smaller than the MSE of the LOHBA algorithm.

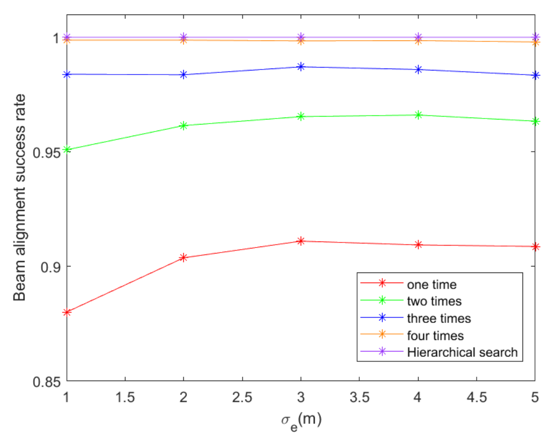

Fig. 7. Beam alignment success rate for different angular deviation under the conventional HS scheme and the proposed method

Fig. 6 shows the impact of the distance and ranging variance on angular deviation. Specifically, the angular deviation decreases by 3 times as the distance increases from 20 meters to 60 meters for $N_t = 256$. Because the distance variance is lower at longer distances, we can predict the angular deviation within a smaller range at those locations. Hence, the proposed algorithm will perform better when VUE is far from BS. In addition, it can be observed that angular deviation increases linearly as distance variance increases from 1 to 5. Therefore, we can select a proper angular deviation for the specific situation to select the initial layer and the corresponding codeword.

As shown in Fig. 7, under different angle deviations, to compare the relationship between the proposed scheme and the beam success rate of hierarchical search, the distance between the BS and the VUE is set to be 60 meters. According to the results in Fig. 6, the best angle deviation value at a distance of 60 meters can be obtained. Therefore, single, double, triple, and 4 times the best angle deviation values are selected for comparison. According to Fig. 7, as the angle deviation value increases, the beam alignment success rate gradually increases.

Fig. 8 compares the initial search level of conventional hierarchical search and our algorithm. Simulation results show that the initial search level of conventional hierarchical search is always the first level, while the initial search level of our proposed method is around the third level. In addition, the initial search level of our proposed method slightly decreases as the distance variance increases. Furthermore, as the angular deviation increases, the initial level of beam alignment is slightly reduced, but it is still higher than the hierarchical search. Therefore, it shows that by flexibly selecting the angular deviation, our algorithm can achieve a compromise between accuracy and cost which takes less beam training.

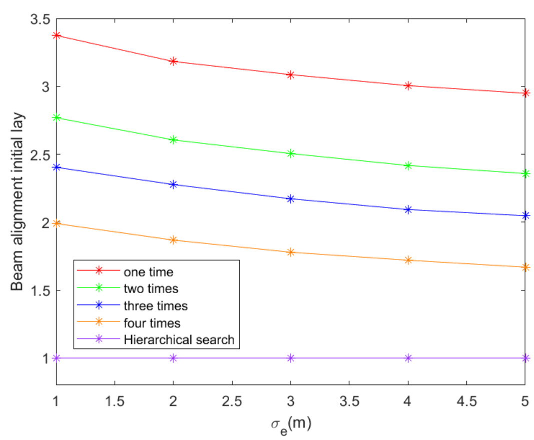

Fig. 8. Initial layer selection for different angular deviation under the conventional HS scheme and the proposed method

V. Conclusion

This paper adopts a generalized hierarchical codebook design method and proposes a millimeter-wave vehicle network beam tracking based on noisy position prediction to reduce training prediction overhead and improve training performance. The simulation results show that the proposed hierarchical search algorithm based on location prediction has almost the same accuracy as the conventional hierarchical search algorithm, but the training cost is less than the latter.

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