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Beam selection based on compressed sensing

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Abstract: An independent radio frequency chain, but this approach will bring excessive cost and power consumption in the millimeter-wave communication massive multiple input multiple output(MIMO) system. In order to solve this problem, hybrid beamforming technology has been spawned, which can achieve good beamforming effect with lower hardware complexity and power consumption. This paper first build the millimeter-wave (mm-Wave) wireless channel simulation model based on the technical report TR 38.901 V16.1.0 published by 3GPP in 2019.12 and explored the beam selection technology based on compressed sensing. Then, using the total transmission rate of the system as an index and utilizing MATLAB to simulate and analyze it. The simulation results show that the total transmission rate of the beam selection system based on compressed sensing increases approximately logarithmically with respect to the number of users K. As the number of users increases, whose beams approach each other in K users to cause multi-user interference, which means that the increase in the total rate may be limited by multi-user interference.
Keywords: MM-Wave, Massive MIMO, Beam Forming, Beam Selection.

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1. INTRODUCTION

Beam forming played a vital role in microwave-based cellular systems. When channel state information (CSI) [1] was available at a base station (BS) equipped with an antenna array, multi-user downlink beam forming can be used to reduce multi-user interference to improve spectrum efficiency. But for the massive MIMO [2] of the mmWave wireless communication system, full CSI feedback from the user to the base station will bring too high feedback overhead. In this case, downlink beam forming with limited CSI feedback can be used to use random (orthogonal) beams in a rich scattering environment together with user selection.

In the TDD system, there are multiple sets of orthogonal beams and multiple time slots. In each time slot, the BS uses a corresponding set of orthogonal beams to transmit pilot or training signals, and each user can select one of the orthogonal beams and feed back its index for selecting the downlink beam. At the BS, the best orthogonal beam set among the multiple sets can be selected according to the sum rate. Although the number of orthogonal beams per group is limited (depending on the number of antennas), the number of active users will be limited. However, as the number of users increases, the better performance can be achieved by using multi-user diversity [3]. In addition, as the

number of orthogonal beams or time slot groups increases, performance can be improved, but training overhead also increases.

Compressive sensing (CS) is introduced to estimate sparse signals or parameters from measurements or observations in large-scale spaces in literature [4]. CS is a powerful tool that can be applied to many issues from image compression to radar applications. In wireless communication, CS is also applied to various sparse multipath channel estimation problems and CSI feedback, for example, for mm wave channel estimation under certain sparseness (or limited scattering) environment [5]. This paper explored a beam selection method that can be performed without using explicit channel estimation. Therefore, in terms of cost (due to the analog beam former) and lower signaling overhead (due to the need for a pilot symbol for beam selection), for mm wave multi-user systems with analog beam formers deploying large antenna arrays, the method may be an attractive solution.

However, the above literatures did not consider lower signaling overhead and low complexity. This paper explored the beam selection technique based on compressed sensing, which can be performed without the use of explicit channel estimation and introduced compressed sensing to estimate sparse signals or parameters from measurements or observations in large-scale spaces. The analysis verifies the performance of the method under the mm wave channel through the simulation platform.

The structure of this paper is as follows: The section II introduced the simulation model. The section III proposed a beam selection algorithm based on compressed sensing. The section IV simulated and verified the proposed scheme and theoretical analysis. The section V mainly summarizes the content of this paper.

2. SYSTEM MODEL

It was assumed that a selected beam can be used in each coherent block or time slot to connect a group of users to the BS. Assuming that the TDD-based system was divided into three stages. The first stage was to establish a connection between the BS and the user through beam selection. The second and third phases were used for downlink and uplink transmission, respectively. This paper only focused on the first stage, which was divided into four sub-stages, as shown in Fig.1:

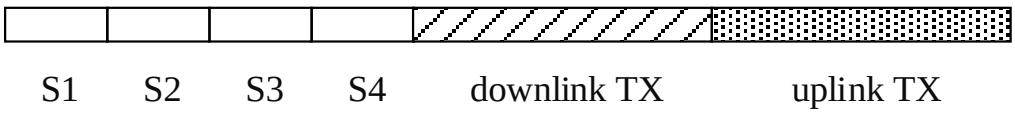

Fig.1 Data transmission process under TDD system

In the first stage, the first two sub-stages would send pilot or training signals, which allowed the BS and the user to select the beam from the code book to be used. The last two sub-phases were to assign the BS beams to users based on the signal to interference plus noise ratio (SINR). The roles of these four sub-stages are summarized as follows:

S1) Downlink training signaling for user beam selection:

S2) Uplink training signaling for BS beam selection:

S3) Downlink transmission, which is to allow the user to select one of the BS beams selected in S2:

S4) Uplink transmission, which send the user's beam selection about the BS through a channel quality indicator (CQI).

3. BEAM SELECTION ALGORITHM BASED ON COMPRESSED SENSING

This section focused on the second sub-stage (S2) of BS beam selection in order to select multiple BS beams for the user without explicit channel estimation.

The BS sends the pilot or training signal indicated by b to the user, and the received signal at user K is:

$$\mathrm{x}_k = \mathrm{H}_k \mathrm{b} + \tilde{\mathrm{n}}_k \tag{1}$$

Under the condition of user path angle separation, there are:

$$\mathrm{c}_k = \sum_{p=1}^{p} h_{k,p}\, \mathrm{a}_B\left(\theta_{k,p}\right) \mathrm{a}_U^T\left(\psi_{k,p}\right) u_k^* \approx h_{k,p(k)} C_k\, \mathrm{a}_B\left(\theta_{k,p(k)}\right) + O\left(\sqrt{\sigma_U}\right) \tag{2}$$

where u_k represents the beamforming vector used for uplink transmission at user k, then the user k received signal is:

$$\begin{aligned} r &= \sum_{\mathrm{K}=1}^{\mathrm{K}} c_k T_k + \mathrm{n} \approx C \sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{a}_B\left(\theta_{k,p(k)}\right) h_{k,p(k)} T_k + \mathrm{n} \\ &= \sum_{\mathrm{K}=1}^{\mathrm{K}} \mathrm{a}_B\left(\theta_{k,p(k)}\right) s_k + \mathrm{n} \end{aligned} \tag{3}$$

where $s_k = h_{k,p(k)} T_k$, therefore

$$\mathrm{w} = \left[\mathrm{w}_{(1)} \ldots \mathrm{w}_{(\mathrm{M(B)})}\right] \tag{4}$$

Assuming that M_B is large enough, and each $\mathrm{a}_B\left(\theta_{k,p}(k)\right)$ can be regarded as one of the approximate column vectors of W. Then, the received signal can be approximately expressed as:

$$\mathrm{r} \approx \mathrm{Ws} + \mathrm{n} \tag{5}$$

among them, W can be regarded as a measurement matrix of size $L_B \times M_B$, and s is the sparse signal vector of size k of size $M_B \times 1$ [6]. In general, $M_B \geq L_B >> K$.

Therefore, the CS method can be used to estimate the K sparse signal s from γ in (5). The following problem can be formulated to estimate s:

$$\min \left\|\hat{\mathrm{s}}\right\|_1 \quad \text{subject to} \left\|\mathrm{r} - \mathrm{W}\hat{\mathrm{s}}\right\|^2 \leq \varepsilon \tag{6}$$

where ε is determined by the noise vector n. Although (4.6) is a convex optimization problem, it is too difficult to find a solution at the cost of computational complexity. There are various low-complexity methods to find approximate solutions including greedy algorithms. However, due to the limited computing power of user equipment, the low complexity method is very attractive for user beam selection. This paper adopts the Orthogonal Matching Pursuit (OMP), which is one of the greedy algorithms [7]. OMP algorithm can use the known measurement matrix W to estimate K sparse signal s in γ from formula (5).

The performance of method s based on CS depends on the properties of the measurement matrix W, for example, the coherence of the measurement matrix or the Restricted isometric Property (RIP). If the measurement matrix W satisfies the RIP of order K, for all K sparse vectors, then:

$$\left(1 - k_K\right)\left\|\mathrm{s}\right\|^2 \leq \left\|\mathrm{Ws}\right\|^2 \leq \left(1 + k_K\right)\left\|\mathrm{s}\right\|^2 \tag{7}$$

where $k, K \in (0,1)$ is an isoaxonometric constant. In order to recover k-Sparses using convex optimization or other greedy algorithms, $2K$ (or 3K) must be small enough. However, since the

adjacent column vectors of the measurement matrix W are highly correlated for large MB, good performance can not be achieved unless the path angles are separated from each other.

As the user path Angle separation condition at the user, similar conditions at BS need to be considered. By the BS path Angle separation condition, we mean the distance between any pair of $\{\theta_{1,p}(1),\ldots,\theta_{K,p}(K)\}$. Greater than or equal to $\max_m|\Theta_m|$, namely:

$$\left|\theta_{k,\hat{p}(k)}-\theta_{k',\hat{p}(k')}\right|\geq \max_m|\Theta_m|, k\neq k' \tag{8}$$

In the BS path Angle separation condition, it have $\left|a_B^H(\theta_{k,\hat{p}(k)})a_B(\theta_{k',\hat{p}(k')})\right|^2\leq\delta_B$ for $k\neq k'$. Assume that the BS path Angle separation condition is true. Then the isometric constant is:

$$k_K=(K-1)\delta_B \tag{9}$$

When $(K-1)\delta_B$ is small enough, it can be seen that W can satisfy RIP under the (9)condition of BS path Angle separation. In this case, K sparse signal s can be estimated by CS based method.

While the CS based method used to select K beams in S2, because BS chooses K beams without associating with any specific user, therefore τK does not have to be orthogonal. Therefore, the length of τK can be shortened. One character is enough to reduce training overhead, which is critical when limiting coherence time.

In S1 for user beam selection at the user, an approximate representation of x_k in formula (1) is available. For convenience, user index k is omitted, so:

$$U=\lfloor u_{(1)}\cdots u_{(M_U)}\rfloor \tag{10}$$

For a large enough M_U, X in formula (1) can be approximately:

$$X=[a_U(\psi_1)\ldots a_U(\psi_P)][\rho_1\ldots\rho_P]^T+\tilde{n}\approx Uq+\tilde{n} \tag{11}$$

where p is the sparse vector of P, the isometric constant under the user path Angle separation condition can be directly obtained. The estimation of P sparse signal q in formula (11) based on CS is adopted, that is $(P-1)\delta_U$.

The concept of CS can be used to estimate s and q in formula (5) and formula (11), respectively, because s and q are very sparse [5]. When sparse s and q are estimated, the beams corresponding to non-zero elements s and q can be used for BS and user beams, respectively. Therefore, the method can be regarded as beam selection combining channel estimation or beam selection without direct channel estimation. The user's beam selection can be summarized as follows:

In S2, each user sends a training signal using the user beam uk during S1.

At BS, the received signal is expressed as formula (5), where s is the sparse vector of K and W is the measurement matrix.

The sparse signal s of K is estimated from γ by OMP algorithm.

From the estimated index of the non-zero elements of s, the BS can decide K beams to communicate with the user.

4. Numerical Simulation

In this section, the compressed sensing beam selection algorithm proposed in this paper is simulated and analyzed, and the simulation tool is MATLAB platform. Setting BS and user to use URA and

code book from ARV beam. When considering a three-partitioned system, assume that the Angle domain of BS path Angle is $[-\pi/3,\pi/3]$ and the angle domain of user path angle is $[-\pi/2,\pi/2]$. The path gain is assumed to be $|h_{k,p}|^2=|h|^2=1$, where the phase of $h_{k,p}$ is independent for all k and p and uniformly distributed on $(0,2\pi)$. Since the beam selection performance in the mm-wave MIMO system depends on various factors (such as, channel, number of antennas in the array, number of beams in the beam and beam selection method). Therefore, this paper first considers the CS-based beam selection method, and then presents the overall performance results with a summation rate.

$$\text{Sum Rate}=\sum_{k\in A}\log_2\left(1+\text{SINR}_{U,k}\right) \tag{12}$$

assume that $\theta_{k,p}$ and $\psi_{k,p}$ are generated independently and uniformly on Θ and Ψ respectively, and set that uplink and downlink have the same SNR. In this paper, the optimal multi-user beamforming with SINR constraint is compared, whose target SINR is the same as the target SINR of the beam selection system in CS [8]. Therefore, the total rate of optimal multi-user beamforming is the same as that of the beam selection system. It is worth noting that the optimal multi-user beamforming also performs power control and the same power is allocated in the beam selection.

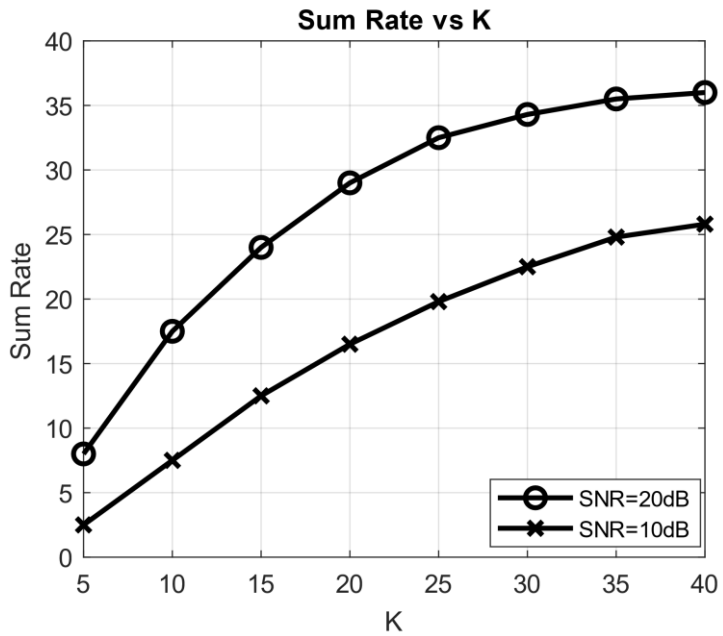

Fig. 2 Relationship between the number of users and the total channel transmission rate under different SNRS

Fig.2 shows the performance of the whole beam selection system facing different number of users when the SNR is 10dB and 20dB respectively. It can be seen from Fig.2 that the total transmission rate increases with the increase of the number of users K, and when K is small, the total rate increases linearly with K. However, this growth becomes slow when K is large, So the total transfer rate is approximately logarithmic with respect to K. In addition, the beam is close to each other within K users and multi-user interference may increase as the number of users increases, which means that the upper limit of the total rate may be limited by multi-user interference.

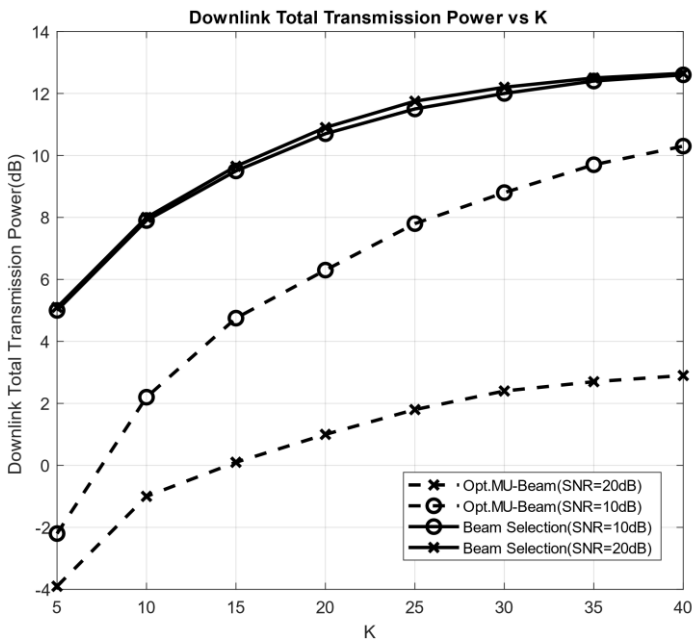

FIG. 3 Relationship between the number of users and transmit power of the two beam selection schemes under different SNR

Fig.3 describes the transmitting power of the optimal beamforming scheme, which has a lower total transmitting power. It can be seen from Fig.3 that the gap between the total transmission power of the beam selection system and the optimal multi-user beam forming system becomes smaller when the SNR is low (such as, 10 dB). In particular, the total transmit power gap is about 2.35 dB and the gap decreases as K increases when the SNR is 10 dB and the number of users is 40. This means that when SNR is low and K is large, the beam selection system can provide reasonable performance with lower system complexity compared to optimal multi-user beam forming.

5. CONCLUSION

This paper constructed a mm wave wireless channel simulation model and massive MIMO technology and hybrid beamforming technology are integrated into the model. In order to focus on the performance of different beam selection algorithms, the Rma-LOS scenario with lower complexity was selected when determining the mm wave wireless channel simulation model. The proposed scheme was simulated and analyzed by simulation tools. The results show that the total transmission rate increases with the increase of the number of users K and the total ratio increases linearly with K when K is small. In addition, compared with optimal multi-user beam forming, the beam selection scheme based on compressed sensing can provide reasonable performance with lower system complexity.

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BIOGRAPHIEA

Dan Wang (baofengjihkd@163.com) received PhD degree in communication and information systems from Shanghai Jiaotong University, in March 2009. In April 2009, she served as an associate professor in School of Information Engineering, Henan University of Science and Technology. As the first author, she won two first prizes and one second prize in the "Henan Province’s Tenth Natural Science Excellent Academic Paper". Mainly engaged in the new generation of wireless communication system theory and key technology, and theory of ultra-wideband wireless communication system. Participated in the National Natural Science Foundation of China, a number of national defense pre-research projects, and hosted the Youth Science Foundation of Henan University of Science and Technology. As the first author, she has published more than 10 academic papers in international and domestic journals and academic conferences.

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