WSDSBL Method for Wideband Channel Estimation in Millimeter-Wave MIMO Systems with Lens Antenna Array

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Abstract —In millimeter wave (mmWave) communication systems, Channel State Information(CSI) is extremely essential for beamforming. The traditional Successive Support Detection (SSD) algorithm can achieve high wideband channel estimation accuracy, but it only used least square (LS) algorithm to recover the detected channel part, the estimation accuracy is low under low SNR regions. To tackle this problem, in this paper, inspired by the classic Support Detection (SD) channel estimation scheme in narrowband, we propose an efficient Wideband Support Detection Sparse Bayesian Learning (WSDSBL) channel estimation scheme. For every subcarrier, we first detect the support of the wideband beamspace channel of the subcarrier, then we use the Sparse Bayesian Learning (SBL) scheme to recover it. Simulation results show that the proposed WSDSBL channel estimation algorithm is better than conventional wideband channel estimation schemes in MSE performance and achievable sum-rate performance, especially in low SNR regions.

Index Terms—Millimeter wave, channel state information, SSD, SBL, wideband channel estimation

I. INTRODUCTION

Recently, Millimeter wave has been widely concerned by industry and academia because of its huge spectrum resources. Due to the high pass loss of Millimeter wave transmission [1], Millimeter wave is usually used in combination with massive MIMO technology. The base station deployed large-scale antennas can provide higher energy efficiency and higher spectrum efficiency [2].

However, mmWave Massive MIMO system is very difficult to realize in practice. For digital systems, each radio-frequency(RF) chain is connected to a single antenna. Although System can achieve best performance, it also faces the unaffordable energy consumption. For analog systems, one RF chain connects all antennas, although energy consumption of system is reduced, the performance of the system is not well. Therefore, the hybrid systems, which includes analog and digital precoders, has emerged [3]. It can reduce energy consumption as much as possible while taking into account system performance. Utilizing the sparsity of millimeter wave propagation in space [4], the channel estimation problem can be turned into the problem of sparse signal recovery. Some existing schemes based compressive sensing(CS) algorithm have been proposed. For example, Orthogonal Matching Pursuit(OMP) [5]-[7], Basis Pursuit De-Noising(BPDN) [8] and some other similar algorithms [9], [10]. However, those schemes are designed for mmWave systems with linear antenna array, the phase shifter network is realized by high-resolution phase shifters, which leads to high energy consumption. To solve this problem, lens antenna array [11] is applied to the system. The lens antenna array consists of an electromagnetic lens and antenna elements located on the focal plane of the lens. In this way, the signal in the space can be concentrated on a few antennas, therefore, the system only needs a small number of RF chains to connect the above antennas. Besides, a 1-bit phase shifter, which greatly reduced the energy consumption and the difficulty of signal processing, was proposed in reference [12] to replace the high-resolution phase shifter. At the same time, reference [12] proposed a channel estimation method named Support Detection(SD) for hybrid systems with lens antenna array.

The schemes above are all designed for narrowband. To achieve higher data rates, mmWave systems are more likely wideband. For wideband systems, a method named simultaneous orthogonal matching pursuit (SOMP) was proposed in reference [13], which supposed that every subcarrier had the same support(an index set of non-zero elements of a sparse vector) in wideband beamspace channel. It firstly estimated the support of wideband beamspace channel of some subcarriers by OMP algorithm, then, it created common support for all subcarriers. Then it recovers the whole beamspace Channel. Some other similar algorithms [14], [15] supposed the common support were proposed recently. However, the assumption of common support is wrong because of beam squint [16]. Considering the problem of beam squint, reference [17] proposed a Successive Support Detection (SSD) algorithm without the assumption of common support. It demonstrated that each path component of the wideband beamspace channel exhibits a unique frequency-varying sparse structure, then, it estimated all sparse path components one by one. Although SSD algorithm performs better than SOMP algorithm. At the end of SSD algorithm, it only used Least Square (LS) algorithm to recover channel vector processed, the estimation accuracy is low under lower SNR regions.

In summary, most of existing wideband channel estimation algorithms can’t work well in real mmWave systems, and the estimation accuracy is very low under

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low SNR regions. However, the uplink SNR is usually low because of the huge path loss and the limit transmit power [18]. To improve the estimation accuracy in low SNR regions, in this letter, inspired by the classical SD algorithm and Sparse Bayesian Learning (SBL) algorithm [19], [20], we propose an efficient Wideband Support Detection Sparse Bayesian Learning (WSDSBL) algorithm. Specifically, for every subcarrier, we firstly detect the support of wideband beamspace channel of the subcarriber, then, we can reduce the dimension of combined matrix by the detected support. Finally, we use SBL algorithm to recover the beamspace channel vector. After all subcarrier beamspace channel vectors recovered, the whole wideband channel state information can be obtained. Simulation results verify that the proposed scheme enjoys higher accuracy and higher sum-rate than existing schemes, especially in low SNR regions.

In the following paper, the model of mmWave MIMO system and the problem of wideband beamspace channel estimation are introduced in Section II. In Section III we elaborate on the proposed WSDSBL algorithm. Simulation results are given in Section IV and we summarize the whole paper in Section V.

II. System Model

As shown in Fig. 1, we consider an uplink time division duplexing (TDD) based wideband mmWave MIMO-OFDM system with M subcarriers. The BS equips N antennas and N_{RF} RF chains to serve K single-antenna users simultaneously. In this section, the wideband beamspace channel will be introduced firstly, and then we will formulate the channel estimation problem.

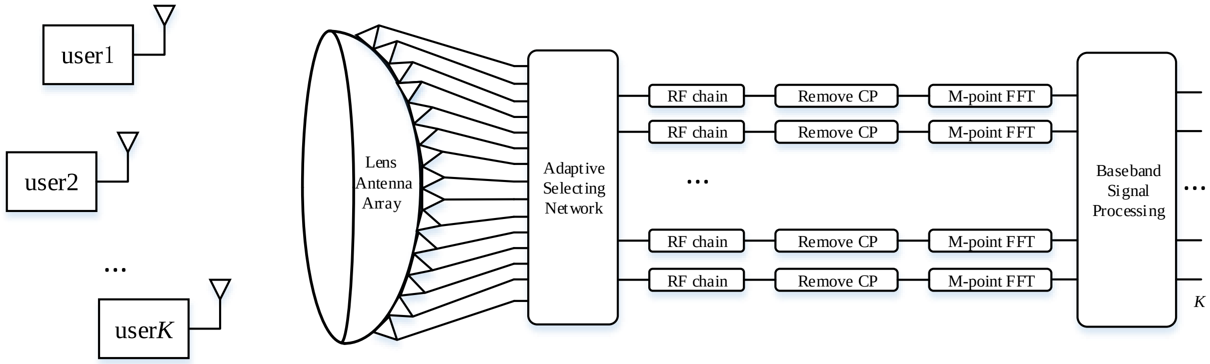

Fig. 1. Wideband mmWave MIMO-OFDM system with lens antenna array

A. Wideband Beamspace Channel

In this letter, we adopt the widely used Saleh-Valenzuela multipath channel model. For the mth subcarrier, $(m=1,2,...,M)$, the $N\times 1$ spatial channel vector can be presented as

$$\boldsymbol{h}_m = \sqrt{\frac{N}{L}}\sum_{l=1}^{L}\beta_l e^{-j2\pi\tau_l f_m}\boldsymbol{\alpha}(\varphi_{l,m}) \tag{1}$$

where N is the number of antennas, L is the number of resolvable paths, β_l and τ_l represent the complex gain and time delay of lth path, respectively, $\varphi_{l,m}$ represents mth subcarriers' spatial direction

$$\varphi_{l,m} = \frac{f_m}{c} d\sin\theta_l \tag{2}$$

where c is speed of the light, d is the antenna spacing which is usually designed according to carrier frequency as $d = c/2f_c$, f_c is the carrier frequency, θ_l is the physical direction of lth path, f_m is the frequency of the mth subcarrier

$$f_m = f_c + \frac{f_s}{M}\left(m-1-\frac{M-1}{2}\right) \tag{3}$$

where f_s is the bandwidth. Finally, $\boldsymbol{\alpha}(\varphi_{l,m})$ represents the array response vector of $\varphi_{l,m}$, For typical uniform linear array

$$\boldsymbol{\alpha}(\varphi) = \frac{1}{\sqrt{N}}\left[e^{-j2\pi\varphi i}\right]_{i\in I(N)} \tag{4}$$

where $I(N) = \{p-(N-1)/2, p = 0,1,2,...,N-1\}$.

As shown in Fig. 1, the lens antenna array can transform spatial channel $\boldsymbol{h}_m$ into beamspace channel $\tilde{\boldsymbol{h}}_m$. From a mathematical point of view, the lens antenna array plays the role of discrete fourier transform (DFT) matrix $\boldsymbol{U}$

$$\boldsymbol{U} = \left[\boldsymbol{\alpha}(\phi_1),\boldsymbol{\alpha}(\phi_2),...,\boldsymbol{\alpha}(\phi_N)\right]^H \tag{5}$$

where $\phi_n = \frac{1}{N}\left(n-\frac{N+1}{2}\right), n = 1,2,...N$ are directions predefined by lens antenna array, then $\tilde{\boldsymbol{h}}_m$ can be presented as

$$\tilde{\boldsymbol{h}}_m = \boldsymbol{U}\boldsymbol{h}_m = \sqrt{\frac{N}{L}}\sum_{l=1}^{L}\beta_l e^{-j2\pi\tau_l f_m}\tilde{\boldsymbol{c}}_{l,m} \tag{6}$$

where $\tilde{\boldsymbol{c}}_{l,m}$ represents lth channel component of mth subcarrier beamspace channel vector

$$\begin{aligned}\tilde{\boldsymbol{c}}_{l,m} &= \boldsymbol{U}\boldsymbol{\alpha}(\varphi_{l,m}) \\ &= \left[\Xi(\varphi_{l,m}-\phi_1),\Xi(\varphi_{l,m}-\phi_2),...,\Xi(\varphi_{l,m}-\phi_N)\right]^T\end{aligned} \tag{7}$$

where $\Xi(i) = \sin N\pi i/\sin\pi i$ is the Dirichlet sinc function, which has the property of signal focusing. As we know, L is usually small in mmWave systems because of the property of mmWave. Therefore, $\tilde{\boldsymbol{h}}_m$ is a sparse vector. we turn the problem of channel estimation into the problem of sparse signal recovery.

B. Wideband Beamspace Channel Estimation Problem Formulation

In the uplink channel estimation phase, K users should transmit the pilot sequences to the BS, we adopt the orthogonal pilot transmission strategy, which is widely used. Each user transmits one pilot in one instant. For a certain user, after M point IFFT and cyclic prefix(CP) adding, user transmits pilot signal to the BS. In the BS, after CP removing and M point FFT, in the instant q, the received signal of mth subcarrier can be presented as

$$\boldsymbol{Y}_{m,q} = \boldsymbol{W}_q \tilde{\boldsymbol{h}}_m s_{m,q} + \boldsymbol{W}_q \boldsymbol{N}_{m,q} \tag{8}$$

where $\boldsymbol{W}_q$ is the adaptive selecting network of size $N_{RF} \times N$, $\boldsymbol{N}_{m,q}$ is the noise vector of size $N \times 1$, $\boldsymbol{N}_{m,q} \sim \mathbb{CN}(0, \sigma^2 \boldsymbol{I}_N)$, σ^2 is the noise power. $s_{m,q}$ is the received pilot signal of mth subcarrier. We assume $s_{m,q} = 1, q = 1, 2, ..., Q$ without loss of generality. Therefore, equation (8) can be rewritten as

$$\boldsymbol{Y}_{m,q} = \boldsymbol{W}_q \tilde{\boldsymbol{h}}_m + \boldsymbol{W}_q \boldsymbol{N}_{m,q} \tag{9}$$

After Q instants of pilots transmission. The received signal of mth subcarrier can be presented as

$$\begin{aligned} Y_m &= \begin{bmatrix} Y_{m,1} \\ Y_{m,2} \\ \cdots \\ Y_{m,Q} \end{bmatrix} = \begin{bmatrix} \boldsymbol{W}_1 \\ \boldsymbol{W}_2 \\ \cdots \\ \boldsymbol{W}_Q \end{bmatrix} \tilde{\boldsymbol{h}}_m + \begin{bmatrix} \boldsymbol{W}_1 N_{m,1} \\ \boldsymbol{W}_2 N_{m,2} \\ \cdots \\ \boldsymbol{W}_Q N_{m,Q} \end{bmatrix} \\ &= \boldsymbol{W}\tilde{\boldsymbol{h}}_m + \boldsymbol{N}_m \end{aligned} \tag{10}$$

where $\boldsymbol{W}$ is the combined matrix of size $QN_{RF} \times N$, $\boldsymbol{N}_m$ is the effective noise received of size $QN_{RF} \times 1$. The whole beamspace channel matrix can be presented as

$$\begin{aligned} \boldsymbol{Y} &= [\boldsymbol{Y}_1, \boldsymbol{Y}_2, ..., \boldsymbol{Y}_M] \\ &= \boldsymbol{W}[\tilde{\boldsymbol{h}}_1, \tilde{\boldsymbol{h}}_2, ..., \tilde{\boldsymbol{h}}_M] + [\boldsymbol{N}_1, \boldsymbol{N}_2, ..., \boldsymbol{N}_M] \\ &= \boldsymbol{WH} + \boldsymbol{N} \end{aligned} \tag{11}$$

we can use classical compressive sensing algorithms to recover beamspace channel. To achieve the satisfying recovery accuracy, the mutual coherence of the combined matrix $\boldsymbol{W}$ should be as small as possible, we can design the adaptive selecting network as 1-bit phase shifter [12], $\boldsymbol{W}$ is randomly selected from $\frac{1}{\sqrt{Q}}(-1, +1)$, the mutual coherence of $\boldsymbol{W}$ is pretty low.

III. WSDSBL-Based Wideband Channel Estimation

In this section, we will introduce Sparse Bayesian Learning algorithm firstly, and the reason why SBL can't be an effective solution will be given, then, Support Detection strategy will be elaborated. Finally, WSDSBL algorithm will be summarized at the end of this section.

A. SBL Algorithm

The problem of sparse signal recovery based on Bayesian framework not only considers the sparse characteristics of the beamspace channel vector, but also takes into account the prior statistical information of the channel vector and the additive noise in the measurement process.

For equation (10), The SBL framework assigns parameterized Gaussian prior to the sparse beamspace channel vector $\tilde{\boldsymbol{h}}_m$

$$p(\tilde{\boldsymbol{h}}_m \mid \boldsymbol{\gamma}) = \prod_{i=1}^{N} (2\pi\gamma_i)^{-1} \exp\left(-\frac{|\tilde{\boldsymbol{h}}_m(i)|^2}{2\gamma_i} \right) \tag{12}$$

where $\boldsymbol{\gamma} = [\gamma_1, \gamma_2, ..., \gamma_N]$ is the hyperparameter, which denotes the variances associated with beamspace channel vector $\tilde{\boldsymbol{h}}_m$, we can observe that as $\gamma_i \to 0$, the associated channel component $\tilde{\boldsymbol{h}}_m(i) \to 0$, Thus, estimation of $\tilde{\boldsymbol{h}}_m$ is converted to estimation of the hyperparameter vector $\boldsymbol{\gamma}$. Thus, the Gaussian likelihood model can be obtained as

$$\begin{aligned} & p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m, \sigma^2) \\ &= (2\pi\sigma^2)^{-\frac{V}{2}} \exp\left(-\frac{1}{2\sigma^2} \left\| \boldsymbol{Y}_m - \boldsymbol{W}\tilde{\boldsymbol{h}}_m \right\| \right) \end{aligned} \tag{13}$$

where σ^2 is the noise variance, $V = QN_{RF}$. Then, the marginal probability density function of $\boldsymbol{Y}_m$ can be obtained as

$$\begin{aligned} & p(\boldsymbol{Y}_m \mid \boldsymbol{\gamma}, \sigma^2) \\ &= \int p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m, \sigma^2) p(\tilde{\boldsymbol{h}}_m \mid \boldsymbol{\gamma}) \\ &= (2\pi)^{-\frac{V}{2}} \left| \boldsymbol{\Sigma}_{\boldsymbol{Y}_m} \right|^{-\frac{1}{2}} \exp\left[-\frac{1}{2} \boldsymbol{Y}_m^T \boldsymbol{\Sigma}_{\boldsymbol{Y}_m}^{-1} \boldsymbol{Y}_m \right] \end{aligned} \tag{14}$$

where $\boldsymbol{\Sigma}_{\boldsymbol{Y}_m} = \sigma^2 I + \boldsymbol{W}\boldsymbol{\Gamma}\boldsymbol{W}^H$, $\boldsymbol{\Gamma} = diag(\gamma_1, \gamma_2, ..., \gamma_N)$, the posterior probability distribution of $\tilde{\boldsymbol{h}}_m$ $p(\tilde{\boldsymbol{h}}_m \mid \boldsymbol{Y}_m; \boldsymbol{\gamma}, \sigma^2)$ follows the Gaussian distribution with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Sigma}_{\tilde{\boldsymbol{h}}_m}$

$$\boldsymbol{\mu} = \frac{1}{\sigma^2} \boldsymbol{\Sigma}_{\tilde{\boldsymbol{h}}_m} \boldsymbol{W}^H \boldsymbol{Y}_m \tag{15}$$

$$\boldsymbol{\Sigma}_{\tilde{\boldsymbol{h}}_m} = \left(\frac{1}{\sigma^2} \boldsymbol{W}^H \boldsymbol{W} + \boldsymbol{\Gamma}^{-1} \right)^{-1} \tag{16}$$

Finally, the recovered sparse channel vector $\hat{\boldsymbol{h}}_m = \boldsymbol{\mu}$. The expectation maximization (EM) algorithm can be used to estimate σ^2 and $\boldsymbol{\gamma}$ through maximizing equation (14), It is equivalent to minimize $-\log p(\boldsymbol{Y}_m \mid \boldsymbol{\gamma}, \sigma^2)$, The cost function $\boldsymbol{L}$ can be obtained by taking negative logarithm on both sides of equation (14)

$$L = \log\left|\boldsymbol{\Sigma}_{Y_m}\right| + \boldsymbol{Y}_m^T \boldsymbol{\Sigma}_{Y_m}^{-1} \boldsymbol{Y}_m \tag{17}$$

we can maximize $E_{\tilde{h}_m|Y_m,\gamma,\sigma^2}\left(p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m,\boldsymbol{\gamma},\sigma^2)\right)$ to obtain estimated value of $\boldsymbol{\gamma}$ after j iterations.

$$\gamma_i^{(j)} = (\boldsymbol{\Sigma}_{\tilde{h}_m})_{i,i} + \mu_i^2 \tag{18}$$

where $p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m,\boldsymbol{\gamma},\sigma^2) = p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m,\sigma^2)p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m)$. We can obtain estimated value of σ^2 after j iterations through maximizing $E_{\tilde{h}_m|Y_m,\gamma,\sigma^2}\left(p(\boldsymbol{Y}_m \mid \tilde{\boldsymbol{h}}_m,\sigma^2)\right)$.

$$(\sigma^2)^{(j)} = \frac{\left\|\boldsymbol{Y}_m - \boldsymbol{W}\boldsymbol{\mu}\right\|^2 + (\sigma^2)^{(j-1)}\Sigma_{i=1}^N\left[1-(\gamma_i^{(j-1)})^{-1}(\boldsymbol{\Sigma}_{\tilde{h}_m})_{i,i}\right]}{V} \tag{19}$$

we can find that the algorithm must perform matrix inversion in equation (16). The dimension of combined matrix $\boldsymbol{W}$ is usually high because of the number of antenna N in mmWave systems. The complexity of SBL-based channel estimation scheme is extremely high. It can't be applied directly in reality. Therefore, we should reduce the dimension of matrix $\boldsymbol{W}$.

B. Support Detection Strategy

Most of the elements of the channel vector $\tilde{\boldsymbol{h}}_m$ are approximately equal to zero. We just need to focus on the elements whose numerical value is bigger relatively. $\tilde{\boldsymbol{c}}_{m,l}$ is the lth component of $\tilde{\boldsymbol{h}}_m$, the support of $\tilde{\boldsymbol{c}}_{m,l}$ can be represented as

$$\boldsymbol{sup}(\tilde{\boldsymbol{c}}_{m,l}) = \left[p_l - \frac{P}{2},\ldots,p_l + \frac{P-2}{2}\right] \tag{20}$$

where p_l denotes the index of element with the largest value of $\tilde{\boldsymbol{c}}_{m,l}$, P is the number of selected index set around p_l . then we can obtain the combined matrix of this selected elements $\boldsymbol{W}_l = \boldsymbol{W}(:,b)_{b\in \boldsymbol{sup}(\tilde{c}_{m,l})}$, the influence of $\tilde{\boldsymbol{c}}_{m,l}$ should be removed

$$\boldsymbol{Y}_m = \boldsymbol{Y}_m - \boldsymbol{W}\tilde{\boldsymbol{C}}_{m,l}^E \tag{21}$$

where $\tilde{\boldsymbol{C}}_{m,l}^E$ is the estimated value of $\tilde{\boldsymbol{c}}_{m,l}$.

$$\tilde{\boldsymbol{C}}_{m,l}^E(i) = \begin{cases} \tilde{\boldsymbol{c}}_{m,l}^e(i), & i \in \boldsymbol{sup}(\tilde{\boldsymbol{c}}_{m,l}) \\ 0, & i \notin \boldsymbol{sup}(\tilde{\boldsymbol{c}}_{m,l}) \end{cases} \tag{22}$$

$$\tilde{\boldsymbol{c}}_{m,l}^e = (\boldsymbol{W}_l^H \boldsymbol{W}_l)^{-1}\boldsymbol{W}_l^H \boldsymbol{Y}_m \tag{23}$$

Above procedures will be repeated L times. Finally, we can get the support of $\tilde{\boldsymbol{h}}_m$

$$\boldsymbol{sup}(\tilde{\boldsymbol{h}}_m) = \bigcup_{l=1}^{L} \boldsymbol{sup}(\tilde{\boldsymbol{c}}_{m,l}) \tag{24}$$

Finally, the combined matrix $\boldsymbol{W}$ after dimension reduction can be presented as

$$\boldsymbol{W}_D = \boldsymbol{W}(:,b), b \in \boldsymbol{sup}(\tilde{\boldsymbol{h}}_m) \tag{25}$$

In the end, we summarize WSDSBL algorithm in Table I.

TABLE I: WSDSBL ALGORITHM

Algorithm: WSDSBL-Based Channel Estimation
Input: Measurement matrix: $\boldsymbol{Y}$; Combined matrix: $\boldsymbol{W}$;
Total number of paths: L ; threshold: η ;
The number of index set selected: P ;
The number of subcarriers M
for $1 \le m \le M$
Initialization: $\boldsymbol{Y}_m^{(1)} = \boldsymbol{Y}_m$, $\tilde{\boldsymbol{C}}_{m,l}^E = \boldsymbol{0}^{N\times 1}, \forall 1 \le l \le L$
while $1 \le l \le L$
compute $p_l = \arg\max_{1\le n\le N}\left\|\boldsymbol{W}(:,n)^H \boldsymbol{Y}_m^{(l)}\right\|$
get $\boldsymbol{sup}(\tilde{c}_{m,l})$ according to (20)
get $\tilde{\boldsymbol{C}}_{m,l}^E$ according to (20,22,23)
get $\boldsymbol{Y}_m^{(l+1)}$ according to (21)
$l = l+1$
end while
get $\boldsymbol{W}_D$ according to (24,25)
mark the number of columns of $\boldsymbol{W}_D$ as D
Initialization: $\gamma_i^{(0)} = 1, \forall 1 \le i \le D$, $\hat{\boldsymbol{\Gamma}}^{(0)} = \boldsymbol{I}_D$, $(\sigma^2)^{(0)} = 1$
while $\left\|\hat{\boldsymbol{\gamma}}^{(j+1)} - \hat{\boldsymbol{\gamma}}^{(j)}\right\|_2 > \eta$ *and* $j < J$
get $\hat{\boldsymbol{\Sigma}}^{(j)}$ according to (16)
get $\hat{\boldsymbol{\mu}}^{(j)}$ according to (15)
get $\boldsymbol{\gamma}^{(j)}$ according to (18)
get $(\sigma^2)^{(j)}$ according to (19)
end while
$\tilde{\boldsymbol{h}}_m^e = \boldsymbol{0}^{N\times 1}$, $\tilde{\boldsymbol{h}}_m^e(\boldsymbol{sup}(\tilde{\boldsymbol{h}}_m)) = \hat{\boldsymbol{\mu}}^{(j)}$
end for
Output: estimated beamspace channel $\hat{\boldsymbol{H}} = [\tilde{\boldsymbol{h}}_1^e, \tilde{\boldsymbol{h}}_2^e, \ldots, \tilde{\boldsymbol{h}}_M^e]$

IV. SIMULATION RESULT

In this section, we will give the simulation results. We consider a typical wideband mmWave system. The base station equips $N = 256$ antennas, the number of RF chains N_{RF} and the number of users K are both 16, the carrier frequency $f_c = 28\text{GHz}$, the complex path gain $\beta \sim \mathcal{CN}(0,1)$, the time delay $\tau_l \sim U(0,20ns)$, the bandwidth $f_s = 2\text{GHz}$, the physical direction of lth path $\theta_l \sim U(-\pi/2,\pi/2)$, the number of paths $L = 3$, the number of index set selected P=8 and the number of max iteration times $J = 50$. Finally, we define the SNR as $1/\sigma^2$.

In the following part, we use two different indicators to evaluate the proposed algorithm. Firstly, we evaluate the proposed algorithm by MSE performance. Secondly. We use sum-rate performance to test it.

Fig. 2 shows the MSE performance comparison against the SNR, where the instants of pilots transmission of each user $Q = 16$. The proposed algorithm performs much better than classical OMP algorithm and SOMP algorithm.

Both two algorithms don't consider the structural features of beamspace channel. SOMP algorithm performs worse when SNR is high. The reason is that SOMP algorithm considered all subcarribers has the same support, which is different in reality. The SSD algorithm, which considers the structural features of beamspace channel, can achieve higher accuracy. But it only uses LS algorithm to recover detected channel part. Therefore, it performs not well in low SNR regions. We can find that the proposed algorithm is better than SSD algorithm. Especially when the SNR is low. Because of the huge path loss of millimeter wave propagation, the uplink SNR is usually low in reality. The advantages at low SNR make the proposed algorithm more practical.

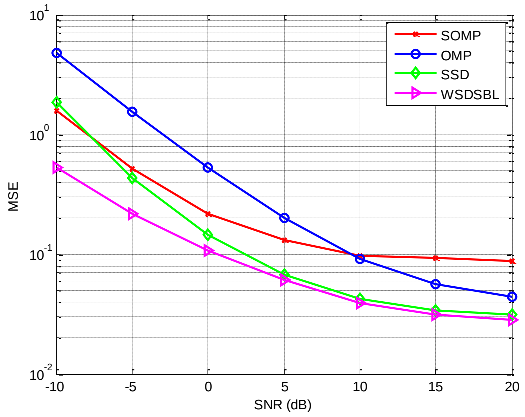

Fig. 2. MSE performance comparison against SNR

Fig. 3 shows the MSE performance comparison against the number Q, where the uplink SNR is equal to 0dB. We can find that the number of instants required by proposed algorithm is much smaller than existing algorithms to achieve the same accuracy. For example, to achieve the accuracy of proposed algorithm estimated by 6 instants, all existing algorithms needs more than 16 instants. The proposed algorithm can achieve satisfying accuracy with reduced pilots overhead.

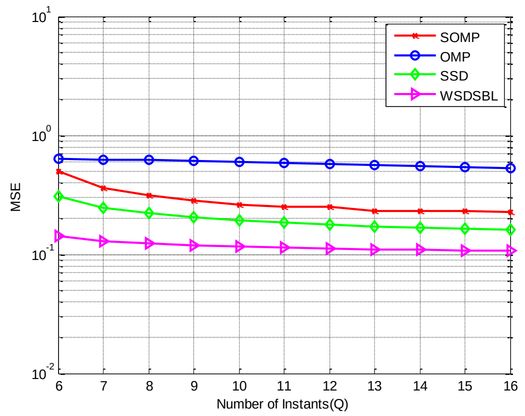

Fig. 3. MSE performance comparison against the number of Q

Fig. 4 and Fig. 5 show the sum-rate performance of wideband beam selection proposed in [16] with different algorithms, where the instants transmission times Q is equal to 16. In Fig. 4, the uplink SNR is -5dB. Using the CSI estimated by proposed algorithm, the system can achieve high sum-rate performance, when uplink SNR is 5dB, the system can achieve higher sum-rate performance, which is very closed to the sum-rate performance using the perfect CSI. Besides, we can find that the advantage of proposed algorithm is more obvious when uplink SNR is low, as shown in Fig. 4.

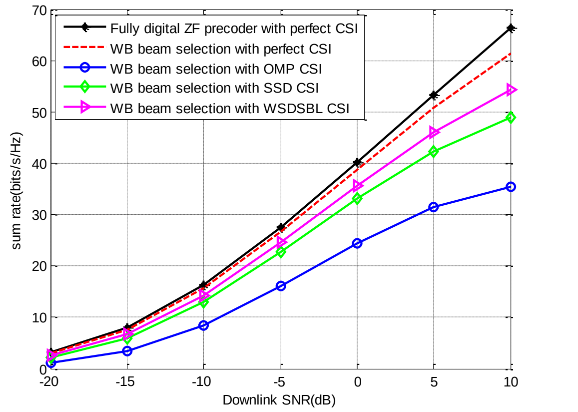

Fig. 4. sum-rate performance comparison against downlink SNR when uplink SNR = -5dB

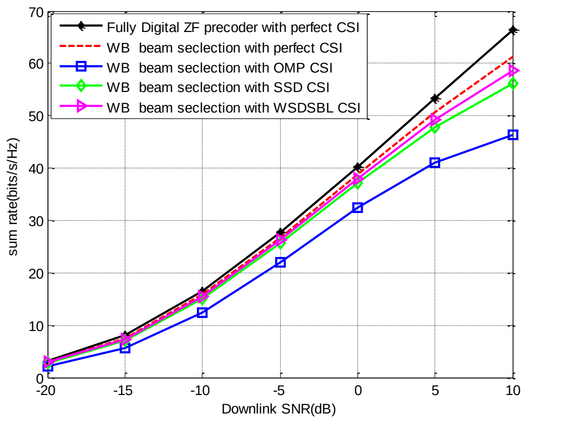

Fig. 5. sum-rate performance comparison against downlink SNR when uplink SNR = 5dB

V. CONCLUSIONS

In this paper, in order to improve the estimation accuracy under low SNR regions, a novel and efficient WSDSBL algorithm for mmWave wideband channel estimation was proposed. Firstly, the support of beamspace channel vector is detected, then, we use SBL algorithm to recover the detected channel part. Compared with the traditional SSD algorithm, the proposed algorithm can improve estimation accuracy efficiently, especially when uplink SNR is low. Simulation results show that the proposed algorithm efficiently improve the performance of traditional algorithms in low SNR regions.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Jicheng Dong and Wei Zhang conducted the research, including ideas formatting, simulation analysis, structure of the whole contents organization. And Jicheng Dong wrote the paper. Bowen Yang and Xihong Sang checked and revised all the content of this research. All authors had approved the final version.

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