SCIENCE CHINA
Information Sciences

August 2020, Vol. 63 180304:1–180304:3
https://doi.org/10.1007/s11432-019-2920-0

• LETTER •

Special Focus on mmWave and Terahertz Wireless Communications for B5G/6G

Joint angle delay estimation in terahertz large-scale array system

Dekang LIU, Zhongshan ZHANG*, Sheng KE, Xue YIN, Xiangyuan BU & Jianping AN

School of Information and Electronics, Beijing Institute of Technology, Beijing 100081*, China*

Received 26 December 2019/Revised 8 March 2020/Accepted 19 May 2020/Published online 15 July 2020

Citation Liu D K, Zhang Z S, Ke S, et al. Joint angle delay estimation in terahertz large-scale array system. Sci China Inf Sci, 2020, 63(8): 180304, https://doi.org/10.1007/s11432-019-2920-0

Dear editor,

To satisfy the growing demand for high data-rate communications, multiple-input-multiple-output (MIMO) technology has been recognized as the most important and fundamental technology in 5th-Generation (5G) wireless communication networks [1]. The future high-speed data networks rely on massive MIMO technology. For some special scenarios, the physical size constraints are no longer as strict as that in the cellular networks, allowing the size of the arrays to become relatively larger such as ships and unmanned aerial vehicles [2]. As the data rate increases, the bandwidth of the traditional microwave frequency will no longer meet the requirements of the practical systems [3]. Fortunately, the terahertz (THz) band enables us to utilize a larger bandwidth, a shorter wavelength, and a smaller antenna size. Except such many advantages, it still faces technical challenges [4, 5]. THz array heavily relies on accurate channel estimation, the tiny error will damage performance.

We investigate a joint angle-delay estimation in THz large-scale array system. Owing to the large size of THz array, it requires a huge computation complexity [6]. To deal with these contradictions, we first give out the system model of a large-scale array system and derive the Cramor-Rao lower bound (CRLB) for the joint angle-delay estimation. Based on this model, a progressively reaching CRLB estimator without grid is proposed. To overcome the huge complexity, we then present a new compressed sensing (CS) structure, and a generalized-approximated-message-passing (GAMP) based algorithm is provided. Numerical results show that the proposed estimator outperforms the multiple-signal-classification (MUSIC) based algorithm. It could reach CRLB in a high signal-to-noise ratio (SNR) regime. The GAMP based algorithm is capable of jointly estimating the angle-delay with a lower complexity.

System model and CRLB. At the base station (BS), a THz array has a size of $D = 128$ mm. While, the signal length is 30 mm which is much smaller than that of the array. We need to rewrite the model of the received signal [7,8]. Considering the signal arrived at m-th antenna with angle θ and delay τ. By discretizing the spectrum f_k, we have

$$\begin{aligned} Y_{m,k} &= H_k X_k \mathrm{e}^{\mathrm{j}2\pi(f_k+f_c)m\frac{d\sin\theta}{c}} \mathrm{e}^{\mathrm{j}2\pi f_k \tau} + W_{m,k} \\ &= S_{m,k}(\theta,\tau) + W_{m,k}, \end{aligned} \tag{1}$$

where, $S_{m,k}(\theta,\tau)$ is signal, and $W_{m,k}$ is noise.

The likelihood function is expressed as follows:

$$p(\boldsymbol{Y},\theta,\tau) = \prod_{m,k} \frac{1}{\sqrt{2\pi\sigma_n^2}} \mathrm{e}^{-\frac{1}{2\sigma_n^2}|Y_{m,k}-S_{m,k}|^2}. \tag{2}$$

* Corresponding author (email: zhangzs@bit.edu.cn)

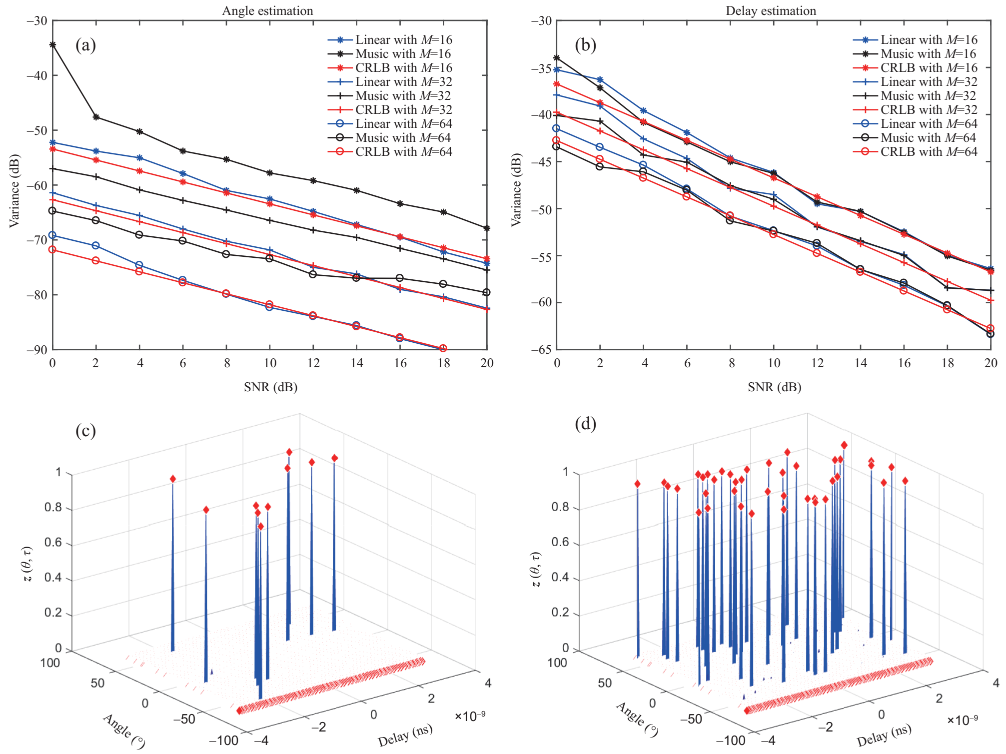

Figure 1 (Color online) Joint angle-delay estimation under 2 methods. (a) Off-grid angle estimation; (b) off-grid delay estimation; (c) GAMP with 10 users; (d) GAMP with 40 users.

Thus, we have the Fisher information matrix:

$$\boldsymbol{I}=\sum_{m,k}\frac{|H_kX_k|^2}{\sigma_n^2}\begin{bmatrix}\left|\dfrac{\partial S_{m,k}}{\partial\theta}\right|^2 & \dfrac{\partial S_{m,k}^H}{\partial\theta}\dfrac{\partial S_{m,k}}{\partial\tau}\\ \dfrac{\partial S_{m,k}^H}{\partial\tau}\dfrac{\partial S_{m,k}}{\partial\theta} & \left|\dfrac{\partial S_{m,k}}{\partial\theta}\right|^2\end{bmatrix}. \quad (3)$$

Progressively reaching CRLB off-grid estimation. For a fixed m and k, we make definitions $\alpha=2\pi(f_k+f_c)m\frac{d\sin\theta}{c}+2\pi f_k\tau$ and $\rho=|H_kX_k|$. The signal can be rewritten as

$$Y_{m,k}=\rho\mathrm{e}^{\mathrm{j}[\alpha+\angle(H_kX_k)]}+w_{m,k}. \quad (4)$$

We use the arctan(x) function to calculate the phase:

$$\hat{\alpha}=\arctan\left(\frac{\rho\sin(\alpha)+\epsilon_s}{\rho\cos(\alpha)+\epsilon_c}\right)=g_{m,k}(\epsilon_s,\epsilon_c), \quad (5)$$

where $\epsilon_s=\Im(w_{m,k})$, and $\epsilon_c=\Re(w_{m,k})$.

Under high SNR, we can approximate $g_{m,k}(\epsilon_s,\epsilon_c)$:

$$g_{m,k}(\epsilon_s,\epsilon_c)\approx\alpha+\frac{\cos\alpha}{\rho}\epsilon_s+\frac{\sin\alpha}{\rho}\epsilon_c, \quad (6)$$

$$g_{m,k}(\epsilon_s,\epsilon_c)\sim N\left(\alpha,\sigma_n^2/|H_kX_k|^2\right). \quad (7)$$

We define $\phi=\sin\theta$ and $\sigma_k=\sigma_n/|H_kX_k|$. Thus, the phase estimation can be written as

$$\hat{\alpha}_{m,k}=2\pi(f_k+f_c)m\frac{d\phi}{c}+2\pi f_k\tau+\eta_{m,k}, \quad (8)$$

where $\eta_{m,k}\sim N(0,\sigma_k^2)$.

We can rewrite $\hat{\alpha}_{m,k}$ as a vector form:

$$\hat{\boldsymbol{\alpha}}=\boldsymbol{F}\,[\tau,\phi]^{\mathrm{T}}+\boldsymbol{\eta}, \quad (9)$$

where $\hat{\boldsymbol{\alpha}}=\mathrm{vec}([\hat{\alpha}_{m,k}])$ is the esitmated phase vector, $\boldsymbol{\eta}=\mathrm{vec}([\eta_{m,k}])$ is the error vector, and $\boldsymbol{F}$ is the observation matrix correspondingly. The noise covariance matrix is $\boldsymbol{\Sigma}_n=\mathrm{blkdiag}([\sigma_0^2\mathbf{1}_{1\times M},\ldots,\sigma_{K-1}^2\mathbf{1}_{1\times M}])$.

Thus, since $\phi(\theta)=\sin\theta$, the variance of τ and θ are

$$\boldsymbol{I}(\hat{\tau},\hat{\theta})=\begin{bmatrix}1&0\\0&\dfrac{\partial\phi}{\partial\theta}\end{bmatrix}\left(\boldsymbol{F}^{\mathrm{T}}\boldsymbol{\Sigma}_n^{-1}\boldsymbol{F}\right)\begin{bmatrix}1&0\\0&\dfrac{\partial\phi}{\partial\theta}\end{bmatrix}. \quad (10)$$

We find that Eq. (10) is consistent with (3) which means the proposed algorithm could reach CRLB.

Compressed sensing based estimation. The M received signals are first combined into M' signals by analog matrix and then are mixed with the local periodic pseudo-random sequence signal $p_{m'}(t)$, and then filtered by a low-pass filter, followed by a low-speed analog-digital-converter (ADC) to obtain a sampling sequence $S_{m'}(n)$. The signal after analog matrix can be written as

$$Y'_{m',k}=\sum_m Y_{m,k}\beta_{m',m}, \quad (11)$$

where $\beta_{m',m}$ represents the phase shifter. The spectrum of the pseudo-random sequence can be written as

$$P_{m'}(f) = \sum_k c_{m',k}\delta(f - k\Delta f). \quad (12)$$

We have the baseband components:

$$S_{m',k'} = \sum_m \sum_k \beta_{m',m} Y_{m,k} c_{k,k'},$$
$$[\boldsymbol{S}]_{M' \times K'} = [\boldsymbol{B}]_{M',M}[\boldsymbol{Y}]_{M,K}[\boldsymbol{C}]_{K,K'}. \quad (13)$$

Thus, we can get the ADC sampling signal:

$$\boldsymbol{s} = \mathrm{vec}(\boldsymbol{S}) = (\boldsymbol{C}^{\mathrm{T}} \otimes \boldsymbol{B})\mathrm{vec}(\boldsymbol{Y}(\theta, \tau)). \quad (14)$$

By meshing (θ, τ), we can rewrite the signal as

$$\boldsymbol{s} = \boldsymbol{T}\boldsymbol{z} + \boldsymbol{n} = \boldsymbol{q} + \boldsymbol{n}, \quad (15)$$

where $\boldsymbol{z}$ is a long vector, in which each element representing whether there exists signal in this grid. Thus, we give out the spare recovery problem. We split the entire space into J grids that do not overlap. For U users, by defining the probability that there is no user as $\lambda = 1 - U/J$, the distribution of z is

$$p(z) = \lambda\delta(z) + (1 - \lambda)\delta(z - 1). \quad (16)$$

Then, we can use the GAMP algorithm to solve this sparse signal recovery problem [9].

Simulation. The described algorithm is verified by numerical simulation. The simulation is carried out for the case of a half-wave array, and the number of antennas is 16, 32, and 64, respectively. Figure 1(a) shows that the off-grid estimation method quickly reaches CRLB and outperforms the root-MUSIC method in angle estimation. With the increase of the SNR, the performance separation increases with the SNR. Figure 1(b) shows that both methods reach CRLB in delay estimation. We can see from Figure 1(c) that the joint angle and delay estimation of 10 users can be realized by using only 2 RF chains. Figure 1(d) shows that if 16 antennas are used, joint angle and delay estimation can be performed for up to 40 users.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant No. 61620106001).

References

1 Li L M, Wang D M, Niu X K, et al. mmWave communications for 5G: implementation challenges and advances. Sci China Inf Sci, 2018, 61: 021301

2 Luo S X, Zhang Z S, Wang S, et al. Network for hypersonic UCAV swarms. Sci China Inf Sci, 2020, 63: 140311

3 Kleine-Ostmann T, Nagatsuma T. A review on terahertz communications research. J Infrared Milli Terahz Waves, 2011, 32: 143–171

4 Han C, Akyildiz I F, Gerstacker W H. Timing acquisition and error analysis for pulse-based terahertz band wireless systems. IEEE Trans Veh Technol, 2017, 66: 10102–10113

5 Liu Q H, Wang Y Z, Fathy A E. A compact integrated 100 Gs/s sampling module for UWB see through wall radar with fast refresh rate for dynamic real time imaging. In: Proceedings of IEEE Radio and Wireless Symposium, Santa Clara, 2012. 59–62

6 Xiong X Y, Deng Z M, Qi W, et al. High-precision angle estimation based on phase ambiguity resolution for high resolution radars. Sci China Inf Sci, 2019, 62: 040307

7 Wang B L, Gao F F, Jin S, et al. Spatial- and frequency-wideband effects in millimeter-wave massive MIMO systems. IEEE Trans Signal Process, 2018, 66: 3393–3406

8 Jian M N, Gao F F, Tian Z, et al. Angle-domain aided UL/DL channel estimation for wideband mmwave massive MIMO systems with beam squint. IEEE Trans Wireless Commun, 2019, 18: 3515–3527

9 Al-Shoukairi M, Schniter P, Rao B D. A GAMP-based low complexity sparse bayesian learning algorithm. IEEE Trans Signal Process, 2018, 66: 294–308