Joint AOA-RSS Fingerprint Based Localization for Cell-Free Massive MIMO Systems

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***Abstract*—Fingerprint based localization is an effective positioning method for rich scattering environments, which has attracted the enormous attention in recent years. In this paper, we propose a novel fingerprint positioning method for cell-free massive multiple-input multiple-output (MIMO) systems. The angle-domain channel power matrix with lots of angle information can be extracted as the arrival-of-angle (AOA) fingerprint by exploiting discrete Fourier transform (DFT) operation. Then we also propose the angle similarity coefficient and the Euclidean distance as the AOA and received signal strength (RSS) fingerprint similarity criterions respectively to evaluate the distance between two fingerprints. Moreover, the K-means clustering algorithm is performed for improving the efficiency of fingerprint matching. Finally, we utilize the weighted K-nearest neighbor (WKNN) algotithm to estimate the location of the user, whose weight can be constructed according to the above fingerprint similarity criterions. The simulation results demonstrate that our proposed joint AOA-RSS fingerprint based location method has the better positioning performance than the methods only consider AOA or RSS fingerprint.**

***Index Terms*—Fingerprint localization, cell-free massive MIMO, angle similarity coefficient, Euclidean distance, WKNN.**

I. Introduction

Nowadays, due to the location information obtained can provide context-aware communication services, wireless localization have paid a lot of attentions especially in the next-generation communication systems [1]. The traditional wireless location techniques follow the assumption that the line-of-sight (LOS) channel is dominant, and then estimate the location by exploiting received signal strength (RSS), time of arrival (TOA), angle of arrival (AOA) or other measurement metrics [2]. While in the non-line of sight (NLOS) scenario with rich scattering, the positioning accuracy of the above method may be degrade significantly.

Since the high positioning accuracy requirements in the rich scattering environment, fingerprint based localization has been widely developed since its wide applicability and high cost-efficiency [3], [4]. The process of fingerprint based localization consists of the offline and online stages. Firstly, the fingerprint database can be built by extracting the unique channel characteristics of the corresponding reference point (RP) as the fingerprint in the offline stage. Then the location of user can be estimated by fingerprint extraction, fingerprint matching and location estimation during the online stage.

Cell-free massive MIMO allows lots of wireless access points (APs) in the network to serve different users with the same time-frequency resources, which is seen as a promising technique for eliminating the boundary effect of cell network in the next-generation communication systems [5]. Moreover, cell-free massive MIMO can also provide higher diversity gain, average throughput and energy efficiency than traditional massive MIMO due to its distributed antenna structure [6].

With the development of the explosive growth of location-based applications, wireless positioning for massive MIMO systems is bound to become an important research direction. In [7], for massive MIMO systems with multiple distributed nodes, the author propose an ESPRIT-based method to achieve 2-D positioning. In [8], a direct localization method has been proposed, which basic idea is exploiting channel characteristics to distinguish LOS from NLOS paths based on a new compressed sensing framework, and then locate users by processing obtained data. The authors in [9] propose the fingerprinting positioning method based on RSS fingerprint by modeling the localization problem as Gaussian process (GP) regression, and compares the positioning performance between distributed massive MIMO and co-located massive MIMO systems. In [10], a supervised machine learning (ML) method based on conventional GP and numerical approximation GP has been proposed to estimate the location of users in distributed MIMO systems from the uplink RSS, and give the comparison of the theoretical and simulation analysis based on the two GP methods.

It is noted that the studies based on fingerprint technique above both exploit RSS information from APs as the fingerprint. However, the channel characteristics in cell-free massive MIMO such as AOA can also be extracted as the fingerprint, since its unique distributed structure leads to the channel contains a lot of angle information. In this paper, we investigate the fingerprint localization for cell-free massive MIMO. To make full use of its signal characteristics, we propose a new fingerprint positioning approach based on AOA and RSS fingerprints. The main contributions of this work lie in the following:

1) We extract the AOA and RSS fingerprint information from the uplink received signal, where the angle-domain channel power matrix can be extracted as the AOA fingerprint by performing discrete Fourier transform (DFT) operation.
2) We propose the angle similarity coefficient to evaluate the degree of similarity between two AOA fingerprints and the Euclidean distance to evaluate the distance between

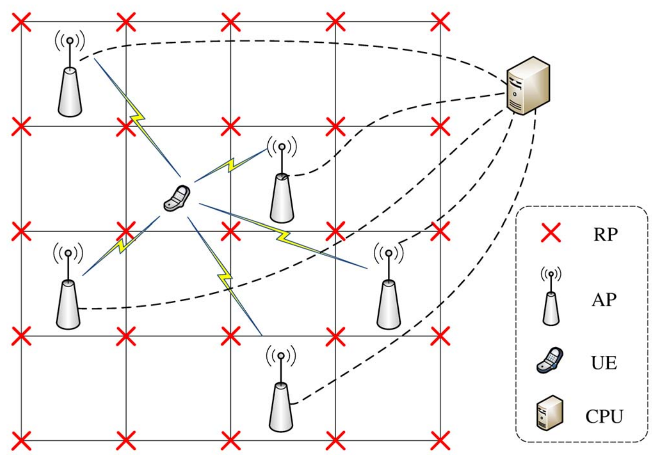

Fig. 1. System Model.

two RSS fingerprints respectively.

3) To reduce the fingerprint matching time and improve the matching efficiency, we adopt the K-means clustering algorithm. Finally, we construct the weight based on the angle similarity and the Euclidean distance, and then estimate the location of user by the weighted K-nearest neighbor (WKNN) method.

II. System Model

Consider a cell-free massive MIMO system where there are N randomly distributed APs, each AP equipped with a uniform linear array (ULA) of M antennas and there are also K RPs in the coverage area, which is illustrated in Fig. 1. All APs obtain the fingerprint data, i.e., channel state information (CSI) or RSS, by collecting the signal sent from different RPs using the single antenna equipment. It is assumed that AP can acquire CSI at each RP by uplink channel estimation. The fingerprint data from all APs can be sent to the central processing unit (CPU) via the fronthaul link, where the CPU can process data and generate the fingerprint database.

A. Channel Model

It is also assumed that the wireless signal propagate along multi-path due to numerous scatterers in the coverage area. Therefore, the $M \times 1$ channel vector from the n-th AP to the k-th RP is given by [11], [12]

$$\mathbf{h}_{nk} = \sqrt{\frac{1}{L}} \sum_{l=1}^{L} \sqrt{\beta_{nk}} \alpha_{nk}^{l} \mathbf{a}\left(\theta_{nk}^{l}\right), \tag{1}$$

where L is the number of scattering paths and $\alpha_{nk}^{l} \sim \mathcal{CN}(0,1)$ represents the small-scale fading of the l-th path. β_{nk} denotes the large-scale fading coefficient. Specifically, three-slope propagation model is adopted in this paper, which is given by [13]

$$\beta_{nk}\,[\mathrm{dB}] = \begin{cases} -81.2, & d_{nk} < 10\mathrm{m} \\ -61.2 - 20\log_{10}\left(\frac{d_{nk}}{1\mathrm{m}}\right), & 10\mathrm{m} \leqslant d_{nk} < 50\mathrm{m}, \\ -35.7 - 35\log_{10}\left(\frac{d_{nk}}{1\mathrm{m}}\right) + \delta_{nk}, & d_{nk} \geqslant 50\mathrm{m} \end{cases} \tag{2}$$

where d_{nk} is the horizontal distance between the n-th AP and the k-th RP[1], δ_{nk} represents the shadowing noise term which follows $\mathcal{CN}\left(0, \sigma_{\delta_{nk}}^{2}\right)$, where $\sigma_{\delta_{nk}} = 8$ dB.

In addition, the array steering vector $\mathbf{a}\left(\theta_{nk}^{l}\right) \in \mathbb{C}^{M\times 1}$ is given by

$$\mathbf{a}\left(\theta_{nk}^{l}\right) = \left[1, e^{-j\frac{2\pi d}{\lambda}\cos\theta_{nk}^{l}}, \cdots, e^{-j\frac{2\pi(M-1)d}{\lambda}\cos\theta_{nk}^{l}}\right]^{T}, \tag{3}$$

where θ_{nk}^{l} is the AOA of the l-th path between the corresponding nodes, d and λ represent the antenna spacing and signal carrier wavelength respectively.

B. Fingerprint Extraction

During the offline stage, the single antenna equipment at the k-th RP transmits a pilot sequence $\mathbf{s}_k \in \mathbb{C}^{\tau\times 1}$ to all APs, where $\|\mathbf{s}_k\|^2 = 1$. Therefore, the received signal vector $\mathbf{Y}_{nk} \in \mathbb{C}^{M\times\tau}$ at the n-th AP is given by

$$\mathbf{Y}_{nk} = \sqrt{P}\mathbf{h}_{nk}\mathbf{s}_k^{H} + \mathbf{N}_n, \tag{4}$$

where P denotes the transmit power, $\mathbf{N}_n \in \mathbb{C}^{M\times\tau}$ is the additive noise matrix which entries are independent $\mathcal{CN}(0,1)$ random variables.

1) AOA Fingerprint Extraction: The AP receives the signal and estimates the corresponding channel by exploiting the common channel estimation methods. It is noted that our focus is to study the positioning performance for cell-free massive MIMO system based on fingerprint information under perfect CSI assumption, and hence the issue occurs during the process of the practical implementation (e.g., channel estimation error) is beyond the scope of this paper. Based on the above discussion, the channel matrix $\mathbf{H}_k \in \mathbb{C}^{M\times N}$ between the k-th RP and all APs can be expressed as

$$\mathbf{H}_k = \left[\mathbf{h}_{1k}, \mathbf{h}_{2k}, \cdots, \mathbf{h}_{Nk}\right]. \tag{5}$$

Next, in order to extract the channel AOA characteristics at each RP, the channel information should be mapped into the angle-domain by applying DFT operation. Hence, we define the DFT of the channel $\mathbf{h}_{nk}$ as $[\mathbf{G}_k]_{:,n} = \mathbf{g}_{nk} = \mathbf{F}\mathbf{h}_{nk}$, where $[\mathbf{F}]_{pq} = e^{-j\frac{2\pi}{M}pq}$ is the (p,q)-th element of the DFT matrix $\mathbf{F} \in \mathbb{C}^{M\times M}$, $\mathbf{G}_k = [\mathbf{g}_{1k}, \mathbf{g}_{2k}, \cdots, \mathbf{g}_{Nk}] \in \mathbb{C}^{M\times N}$ represents the angle-domain channel response matrix, where the (p,q)-th entry can be given by

$$\begin{aligned} [\mathbf{G}_k]_{pq} =& \sqrt{\frac{1}{L}} \sum_{l=1}^{L} \sqrt{\beta_{qk}} \alpha_{qk}^{l} e^{-j\frac{M-1}{2}\left(\frac{2\pi}{M}p + \frac{2\pi d}{\lambda}\cos\theta_{qk}^{l}\right)} \\ &\cdot \frac{\sin\left[\left(\frac{2\pi}{M}p + \frac{2\pi d}{\lambda}\cos\theta_{qk}^{l}\right)\frac{M}{2}\right]}{\sin\left[\left(\frac{2\pi}{M}p + \frac{2\pi d}{\lambda}\cos\theta_{qk}^{l}\right)\frac{1}{2}\right]}. \end{aligned} \tag{6}$$

The most important feature of the fingerprint information is its high reliability and stability. That is to say, the random channel fluctuation caused by the small-scale fading should be

[1]For simplicity, we ignore the height difference between the AP and the user, and the case that considers the height difference can be left for our future studies.

suppressed. Hence, the angle-domain channel power matrix for the k-th RP can be defined as [14]

$$\boldsymbol{\Theta}_k \triangleq \mathbb{E}\left\{\mathbf{G}_k \odot \mathbf{G}_k^*\right\} \in \mathbb{R}^{M\times N}, \tag{7}$$

where $\odot$ denotes the operation of Hadamard product, and $\left[\boldsymbol{\Theta}_k\right]_{pq} \triangleq \mathbb{E}\left\{\left|\left[\mathbf{G}_k\right]_{pq}\right|^2\right\}$ is the (p,q)-th element of the angle-domain channel power matrix. It is worth noting that the angle-domain channel power matrix provides an efficient description on the AOA and the channel power distribution in angle-domain, which can also be easily extracted by exploiting DFT operation and Eq. (7), thus we regard the angle-domain channel power matrix as the dominating fingerprint information to achieve accurate positioning for cell-free massive MIMO systems.

2) RSS Fingerprint Extraction: After the n-th AP receives the signal $\mathbf{Y}_{nk}$, we can obtain RSS value p_{nk} from the n-th AP to k-th RP, which is given by [10]

$$\begin{aligned} p_{nk} &= \left\|\mathbf{Y}_{nk}\right\|_F^2 = \left\|\sqrt{P}\mathbf{h}_{nk}\mathbf{s}_k^H + \mathbf{N}_n\right\|_F^2 \\ &\approx \left\|\sqrt{P}\mathbf{h}_{nk}\mathbf{s}_k^H\right\|_F^2 = P\left\|\mathbf{h}_{nk}\right\|^2. \end{aligned} \tag{8}$$

We note that RSS also fluctuates randomly due to the small-scale fading in wireless channel. This phenomenon above can be reduced by averaging out the small-scale fading over multiple slots, which is known as channel hardening [9]. Based on the assumption above, the RSS can be further expressed as $p_{nk} \approx P\mathbb{E}\left\{\left\|\mathbf{h}_{nk}\right\|^2\right\} = PM\beta_{nk}$, which indicates the RSS is proportional to large-scale fading coefficient β, and further shows that it is inversely proportional to distance d. The RSS varies from the distance, i.e., each location has the unique RSS vector. Hence, the RSS can also be regarded as the fingerprint in another dimension. Taking the RSS fingerprint as angle-domain channel power matrix fingerprint supplement, the accuracy of positioning can be further improved. Thus, we have the RSS vector related to the k-th RP $\mathbf{p}_k = \left[p_{1k}, p_{2k}, \cdots, p_{Nk}\right]^T \in \mathbb{R}^{N\times 1}$, and then the RSS matrix related to all RPs can be expressed as

$$\mathbf{P} = \left[\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_K\right] \in \mathbb{R}^{N\times K}. \tag{9}$$

III. Fingerprint Similarity Criterion

After fingerprint extracting, we note that the location estimation issue can be transformed into pattern recognition problem consisting of the similarity relationship between two fingerprints and the mapping relationship between the distance of fingerprint and physical distance. In this paper, we consider two fingerprint similarity criterions since two different types of fingerprints we exploited.

A. Angle Similarity Coefficient

As the dominating fingerprint, the angle-domain channel power matrix contains a wealth of angle information, thus we take the angle similarity coefficient as the fingerprint similarity criterion, which can be given by

$$\begin{aligned} \mathrm{AS}\left(\boldsymbol{\Theta}_p, \boldsymbol{\Theta}_q\right) &= \frac{1}{N}\sum_{n=1}^{N}\mathrm{AS}_n\left(\boldsymbol{\Theta}_p, \boldsymbol{\Theta}_q\right) \\ &= \frac{1}{N}\sum_{n=1}^{N}\frac{\left[\boldsymbol{\Theta}_p\right]_n^T\left[\boldsymbol{\Theta}_q\right]_n}{\left\|\left[\boldsymbol{\Theta}_p\right]_n\right\|\left\|\left[\boldsymbol{\Theta}_q\right]_n\right\|}, \end{aligned} \tag{10}$$

where $\mathrm{AS}_n\left(\boldsymbol{\Theta}_p, \boldsymbol{\Theta}_q\right)$ represents the angle similarity coefficient between the p-th and the q-th RPs related to the n-th AP.

From Eq. (10), we observe that the angle similarity coefficient represents the degree of correlation between AOA information catched by two different fingerprints. When the two AOA fingerprints have high degree of correlation, the angle similarity coefficient tends to be 1, and the opposite tends to be 0. In other words, the angle similarity coefficient is a monotone increasing function of the degree of correlation.

B. Euclidean Distance

For RSS fingerprint, the Euclidean distance is most commonly used to measure the degree of correlation between two different fingerprints. The Euclidean distance of two fingerprints related to the p-th and the q-th RPs can be represented as [15]

$$\mathrm{ED}\left(\mathbf{p}_p, \mathbf{p}_q\right) = \sqrt{\sum_{n=1}^{N}\left|p_{np} - p_{nq}\right|^2}. \tag{11}$$

We notice that the Euclidean distance decreases with increasing of the correlation between two fingerprints, i.e., it is a monotone decreasing function of the correlation, which is the opposite of the angle similarity coefficient. In order to combine two different fingerprints, two fingerprint similarity criterion should be unified. Hence, we adopt the reciprocal of the Euclidean distance $1/\mathrm{ED}\left(\mathbf{p}_p, \mathbf{p}_q\right)$ as the similarity criterion in this paper.

IV. Fingerprint Location Estimation

We propose AOA-RSS based fingerprint location method in this section, which mainly relies on the AOA fingerprint, supplemented by the RSS fingerprint to achieve user positioning. Furthermore, in order to improve the fingerprint matching speed, during the online stage, the K-means clustering algorithm is introduced in our proposed method. Then, we will give the detailed location estimation algorithm in the following subsection.

A. Proposed Location Estimation Algorithm

The flow diagram of the fingerprint positioning method is demonstrated as Fig. 2, which consists of the offline stage and the online stage.

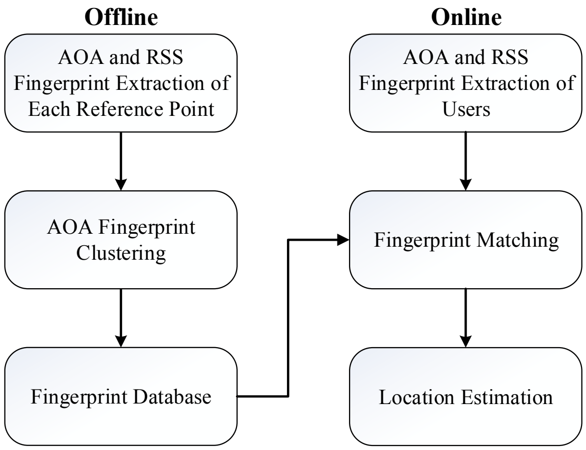

Fig. 2. The flow diagram of the fingerprint positioning method.

1) Offline Stage: During the offline stage, the fingerprint database is expected to built by extracting the feature information of the RPs as the fingerprint, which for making preparation for pattern matching in the online stage. Moreover, to reduce the time of fingerprint matching and enhance the efficiency of location algorithm, we perform the preprocessing of the angle-domain channel power matrix fingerprint by employing the K-means clustering algorithm. The K-means method can partition large fingerprint data with high similarity coefficient into the same cluster, and it is widely used in data processing due to the low computational complexity [16]. The specific steps of the offline stage are listed as follows:

Step1: Dividing the target area into multiple grids uniformly as the RPs for fingerprint extraction.

Step2: Collecting and transmitting the angle-domain channel power matrix and the RSS vector related to all RPs, i.e., $\mathbf{\Theta} = [\mathbf{\Theta}_1, \mathbf{\Theta}_2, \cdots, \mathbf{\Theta}_K] \in \mathbb{R}^{M \times NK}$ and $\mathbf{P}$ to the CPU.

Step3: Dividing the angle-domain channel power matrix fingerprint into N_c clusters, where the angle-domain channel power matrix of the n_c-th cluster center can be expressed as

$$\mathbf{\Theta}_{n_c}^{cen} = \frac{1}{|A_{n_c}|} \sum_{i \in A_{n_c}} \mathbf{\Theta}_i, \tag{12}$$

where $|A_{n_c}|$ denotes the number of RPs in the n_c-th cluster.

Step4: After the fingerprint clustering, the fingerprint database can be formed in the CPU.

2) Online Stage: During the online stage, the fingerprints of the user to be located are matched to the clustered fingerprints in the fingerprint database. Since the K-means clustering algorithm we used in the offline stage, the efficiency of fingerprint matching can be enhanced significantly. The detailed steps of the online stage are shown as follows:

Step1: Extracting each user's fingerprint information $\mathbf{\Theta}_{UE}$ and $\mathbf{p}_{UE}$ according to the received signal.

Step2: Calculating the similarity coefficient AS $\left(\mathbf{\Theta}_{UE}, \mathbf{\Theta}_{n_c}^{cen}\right)$ for $n_c \in \{1, 2, \cdots, N_c\}$ and finding N_c^{sel} clusters with the largest angle similarity coefficient by sorting the calculated results.

Step3: Calculating the similarity coefficient of the user's angle-domain channel power matrix fingerprint and the fingerprint of each RP in the cluster selected in **Step2**, i.e., AS $\left(\mathbf{\Theta}_{UE}, \mathbf{\Theta}_{n_c^{sel}}^{i}\right)$ for $n_c^{sel} \in \left\{1, 2, \cdots, N_c^{sel}\right\}$, $i \in \left\{1, 2, \cdots, \left|A_{n_c^{sel}}\right|\right\}$ where $\left|A_{n_c^{sel}}\right|$ denotes the number of RPs in this cluster. Then finding the $N_{RP}^{\max}$ RPs with the largest angle similarity coefficient.

Step4: Calculating the reciprocal of the Euclidean distance of the RSS fingerprint between the user and each RP selected in **Step3**.

Step5: Exploiting the WKNN algorithm to calculating the location estimation, which is described in detail in the following subsection.

B. WKNN Location Estimation Algorithm

The WKNN location estimation algorithm is exploited to achieve user positioning. It is worth noting that the WKNN method is the improved version of the KNN algorithm, which takes the distance or similarity correlation between the user and different RPs into consideration. Hence, fewer RPs can be used than KNN to provide more accurate positioning services. The WKNN location estimation can be given by

$$(\hat{x}, \hat{y}) = \sum_{i=1}^{N_{RP}^{\max}} \varpi_i \left(x_i, y_i\right), \tag{13}$$

where (x_i, y_i) is the coordinate of the i-th selected RP, ϖ_i represents the weight coefficient of the i-th RP which must meet the following condition: $\sum_{i=1}^{N_{RP}^{\max}} \varpi_i = 1$.

Theoretically, the greater the similarity coefficient of two fingerprints are, the closer they are physically to each other. In fact, the results obtained are not desired due to the complexity of wireless transmission. That is to say, the two fingerprints with the largest similarity coefficient may not be the closest in the physical space. Hence, the RSS fingerprint is used as the metric for the second dimension in the final WKNN location method to modify the weight coefficient which only considers the AOA fingerprint information. Specifically, we adopt the strategy of focusing on the AOA fingerprint and supplemented by the RSS fingerprint in the final location method. The weight coefficient of the i-th RP can be constructed as

$$\varpi_i = \frac{\text{AS}\left(\mathbf{\Theta}_{UE}, \mathbf{\Theta}_i\right) \cdot 1/\text{ED}\left(\mathbf{p}_{UE}, \mathbf{p}_i\right)}{\sum_{i=1}^{N_{RP}^{\max}} \text{AS}\left(\mathbf{\Theta}_{UE}, \mathbf{\Theta}_i\right) \cdot 1/\text{ED}\left(\mathbf{p}_{UE}, \mathbf{p}_i\right)}. \tag{14}$$

From Eq. (14), we note that ϖ_i captures the angle similarity relationship and the Euclidean distance between the user and the selected RPs. Compared with the case where the angle similarity relationship (i.e., the angle-domain channel power matrix fingerprint) is only considered, the proposed method can reduce the impact of the above issues and further improve the performance of positioning.

C. Complexity Analysis

In this subsection, the complexity analysis of fingerprint matching for our proposed joint AOA-RSS fingerprint location method is provided. Since the fingerprint extraction

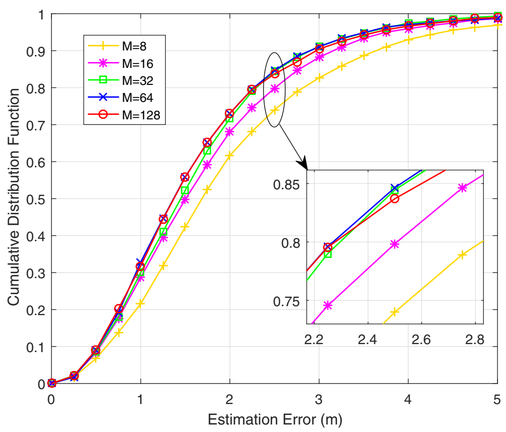

Fig. 3. Cumulative distribution function (CDF) of the location estimation error with different number of AP antennas M for $\eta = 5$.

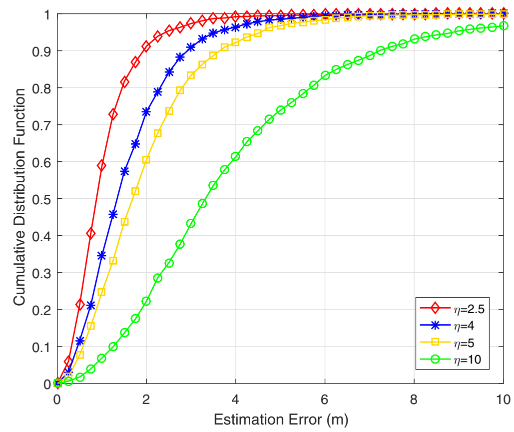

Fig. 4. CDF of the location estimation error with different RP intervals η for $M = 8$.

and clustering are completed in the offline stage, we do not consider this part of complexity for the time being. From Eq. (10) and Eq. (11), we can obtain the complexity of the online matching stage, which is given by $\mathcal{O}\left(3MN\left(N_c + KN_c^{sel}/N_c\right) + NN_{RP}^{\max}\right)$ where $3MN$ denotes the computations for each angle similarity coefficient calculation, N_c is the operation of finding out the largest similarity coefficient comparing with N_c cluster centers, KN_c^{sel}/N_c is the angle similarity matching between the user and each RP in the N_c^{sel} clusters, the latter N and $N_{RP}^{\max}$ represent the computations for each Euclidean distance calculation and the number of selected nearest RPs.

On the other hand, when the AOA fingerprint is considered only, the complexity of the online stage is $\mathcal{O}\left(3MN\left(N_c + KN_c^{sel}/N_c\right)\right)$, which missing the last term compared with the proposed method. It can be seen that the complexity has not increased so much due to the value of the last term $NN_{RP}^{\max}$ is not large.

V. Simulation Results

The simulation results are provided in this section to quantitatively analyze the positioning performance of the joint AOA-RSS based fingerprint location method and compare with the cases that only consider AOA or RSS fingerprints. We first briefly describe the parameters setup in the following subsection.

A. Parameters Setup

Assuming a cell-free massive MIMO system, which all APs and users are randomly distributed in a 100×100 m^2 square area. Moreover, we set the antenna spacing of the ULA to $\frac{\lambda}{2}$ and the RP interval for the fingerprint sampling is set as η. The specific parameters setup is listed in Table I.

B. Simulation Results and Discussions

Fig. 3 illustrates the accuracy of positioning for our proposed joint AOA-RSS fingerprint location approach with different number of AP antennas. It can be observed that

TABLE I
Parameters Setup for the Simulation

Parameters	Value
The number of APs N	10
The number of scattering paths L	10
The number of users	20
The single-side angle spread	4°
The noise power	-96 dBm
The transmit power	100 mW
The number of random realizations of the AP/user locations	100
The number of random realizations of the channel	100
The total number of clusters N_c	15
The number of clusters to be selected with the largest similarity coefficient N_c^{sel}	3
The number of RPs to be selected with the largest similarity coefficient selected $N_{RP}^{\max}$	4

the performance of positioning improves with the number of antennas M increasing, and then degrades slightly when M increases beyond a specific value, here the value is 64. That is to say, the positioning performance for our proposed method can be improved by appropriately increasing the number of AP antennas M. Specifically, we can find that this method can provide 84.65% reliability for 2.5 m accuracy when $M = 64$, and 74% reliability even when $M = 8$, which indicates the advantage of the proposed joint AOA-RSS fingerprint location method.

Fig. 4 presents the impact of the RP interval on the positioning accuracy for the proposed method. As shown in Fig. 4, for the same accuracy, the smaller the RP interval, the better the positioning performance. When $\eta = 5$ m, the location method offers 60.6% reliability for 2 m accuracy. However, when $\eta = 2.5$ m, 91.2% reliability for the same accuracy requirement can be provided. Nevertheless, the small RP interval leads to an increase in the number of RPs, which further results in more fingerprints to be collected and matched in the offline and online stages respectively. In other words, the overhead of the method increases with decreasing of the interval, thus we have to make a compromise between overhead and positioning performance according to the actual requirement.

Fig. 5 compares the positioning performance of different fingerprint location methods under the same condition, including

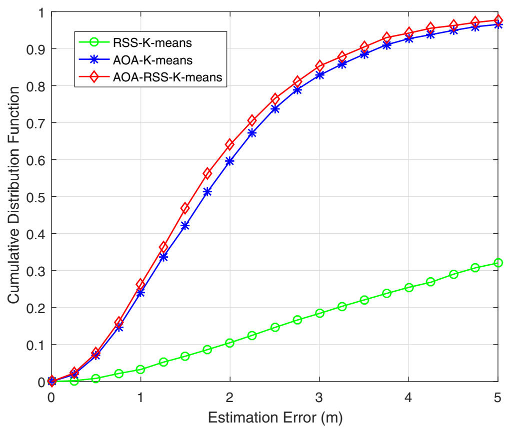

Fig. 5. CDF of the location estimation error with different fingerprint location methods for $M = 8$, $\eta = 5$.

the methods that only consider the RSS fingerprint and the AOA fingerprint. Since these two methods both exploit the K-means clustering algorithm during the offline stage, thus for the convenience of expression, the two methods can be named as "RSS-K-means" and "AOA-K-means" respectively. We observe that our proposed joint AOA-RSS method can provide the best positioning performance, the AOA-K-means is the next and the performance of the RSS-K-means is the worst. This is because AOA fingerprints are more stable than RSS fingerprints in the multi-path transmission environment. Furthermore, the proposed method is mainly based on the AOA fingerprint, supplemented by the RSS fingerprint, which can effectively combine the advantages of the two and further improves the positioning performance.

VI. Conclusion

In this paper, we propose a joint AOA-RSS fingerprint based location method for the cell-free massive MIMO systems. The angle-domain channel power matrix which contains the AOA information of the channel has been extracted as the dominating fingerprint. We also extract the RSS fingerprint as a supplement to the AOA fingerprint to further improve the positioning performance. Based on this, the angle similarity and the Euclidean distance are proposed to assess the degree of similarity of the AOA and the RSS fingerprint respectively. Moreover, the K-means clustering algorithm is exploited to improve the efficiency of the fingerprint matching in the online stage. Then the WKNN location algorithm is used to estimate the final result of positioning, where the weight can be constructed based on the angle similarity and the Euclidean distance. The simulation results indicate that the proposed joint AOA-RSS fingerprint based location method can achieve the better positioning performance than the method that the AOA or RSS fingerprint considered only. Furthermore, the performance can be enhanced by increasing the number of AP antennas or decreasing the RP interval appropriately, which provides theoretical basis for practical implementation deployment.

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