Performance Analysis of DoA Estimation for FDD Cell Free Systems Based on Compressive Sensing Technique

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Abstract—**The concept of cell free (CF) massive MIMO systems is a prospective fifth generation communication technology that effort with base stations for the privilege of user-centric coverage. Most studies on the CF massive MIMO system in the past imply that systems that use time division duplexing (TDD), even despite the systems using frequency division duplex (FDD) predominate in today's wireless communications. When the number of antennas increases in FDD systems, channel state information (CSI) collection and feedback overhead become major issues. In order to mitigate these issues, we make use of the condition that the so-called uplink and downlink multipath components are comparable. Base station takes use of the angle reciprocity may immediately obtain information on channel parameters from the uplink training signal. In this paper, for CF massive MIMO system based on FDD, we provide compressive sensing (CS) of directions of arrival (DoAs) estimation approach of access point cooperation based on the channel parameters. The suggested estimation approach outperforms the established subspace-based technique, according to simulation findings. Additionally, we showed that the results of our compressive sensing estimator against the conventional estimation method. The former demonstrates way far better outcome and performance accordingly than the latter.**

Keywords—**cell free massive MIMO systems, compressive sensing, DoA estimation, FDD systems**

I. INTRODUCTION

The 5G wireless systems have successfully shown the outstanding performance over the fourth communication generation such as 4G LTE systems. In many aspects, for instance, the capacity and spectrum enhancement besides the energy efficiency as well. The main reason for that improvement in the overall performance can be attributed to exploiting and utilizing the concept of massive MIMO architecture in its design [1, 2].

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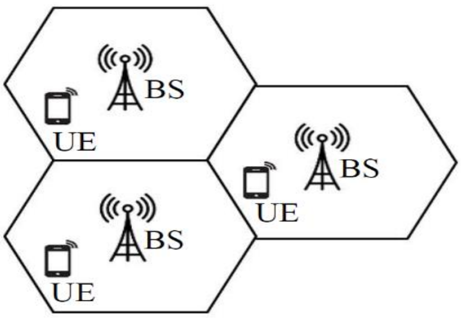
More precisely and accurately the upgraded version which is CF massive MIMO system, which has drawn academic researchers as well as industries significant attentions recently due to their ability to overcome the phenomena of the inter cell interference (ICI) and a recurrent switching for rapid users movement, which both can be occurred due to the small size of the cells as well as many boundaries among them [3, 4]. In CF massive MIMO system, many base stations (BSs) are deployed in locations that are not necessarily determined by the local cells and cooperatively serve multiple users as shown below in Fig. 1, where Fig. 1(a) represents a traditional cellular system in which each cell has one BS serve multiple users (UE) and (b) represents a CF system in which all BS are connected to a central processing unit (CPU) and serve all users. In other words, many BSs serve cooperatively less number of mobile station in the system concurrently, with the same band, they provide uniformly great quality of services and with no handovers. The BSs are connected to a centralized unit to be notified of numbers and locations of the users and more important the updated CSI [5, 6].

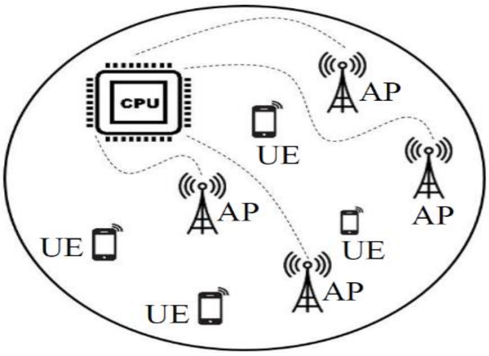
Cell-free massive MIMO systems are a new paradigm in wireless communication that have the potential to greatly improve network capacity, coverage, and energy efficiency. Unlike traditional cellular networks where each cell has a BS, in cell-free massive MIMO, a large number of distributed access points (APs) or antennas are placed throughout the coverage area. These APs can work cooperatively to transmit and receive signals to and from mobile users, which enables higher data rates and better coverage. By using many antennas distributed throughout coverage area, CF massive MIMO system can provide high spatial coverage and capacity. This is especially useful in areas with high user density or in environments with challenging propagation conditions [6, 7].

Cell-free massive MIMO systems can effectively mitigate interference by using the large number of antennas to steer the beamforming in a way that minimizes interference. By using distributed APs, cell-free massive

MIMO systems can significantly reduce energy consumption compared to traditional cellular networks. This is because distributed APs can use less transmit power to achieve the same level of coverage [7–9]. Cell-free massive MIMO systems are highly scalable, and can be easily expanded or modified to meet changing network demands. Some of the challenges associated with cell-free massive MIMO systems include channel estimation, signal processing, and backhaul requirements for the distributed APs. Nevertheless, recent research has shown that cell-free massive MIMO systems have the potential to significantly enhance the performance of wireless communication networks and are potential technologies for the upcoming wireless communications networks [4, 10]. Furthermore, that feature of using multiple antenna at each AP grants the key benefit, i.e., channel hardening properties as well as favorable propagation. As a results of that, the cell-free massive MIMO systems would be able to manage inter cell interference, resulting in substantial improvement in both energy and spectral performance [11].



(a) cellular network



(b) cell free network

Figure 1. Demonstrating the difference (a) cellular network and (b) CF massive MIMO network.

To decrease the training overhead of CSI acquisition for FDD massive MIMO systems, the authors in [12] developed a weighted l_1 minimization algorithm to exploit partial channel support information due to sparsity structure of massive MIMO channel. The authors in [13], proposed a non-orthogonal pilot scheme to do channel estimation based on compressive sensing technique. They assumed two stage algorithm, one for channel estimation based CS technique and the other for feedback tracking. The authors in [14] developed an efficient algorithm to acquire CSI in FDD massive MIMO system. They used CS method to estimate the channel by exploiting the sparsity structure of massive MIMO channel in angular domain representation. In addition, they assumed the channel is spatially correlated.

Kim and Shim [15] proposed an algorithm based on gradient descent method to obtain the CSI from the uplink signal in cell free massive MIMO systems. They assumed FDD system and exploit the angle reciprocity to acquire the channel in the downlink phase. Almosa *et al.* [16] proposed an algorithm to do transmit beamforming based on partial CSI by exploiting angle reciprocity in FDD massive MIMO systems. They used traditional subspace method to obtain the DoAs. We utilize the feature that the multipath coefficients in the uplink (UL) and downlink (DL) channels, i.e., the complex gain and angle, are similar. This property, subsequently called as angle reciprocity, which is being satisfied even for the FDD systems since the carrier frequencies of UL and DL are not far different from each other [17]. The following equation can be used to describe the dominant direction for the downlink using the uplink as follow [16]:

$$\theta_{Downlink} = \theta_{Uplink} + \Delta\theta, \tag{1}$$

where θ_{Uplink} and $\theta_{Downlink}$ are the azimuth or elevation direction of arrival in the uplink and downlink, $\Delta\theta$ refers to the angular disturbance modelled as Laplace variable [16, 18]. In this paper, we present an efficient algorithm for DoAs estimation in CF massive MIMO system based on FDD. Specially inspired by priori knowledge of channel reciprocity in angular domain for uplink and downlink channels, we proposed a different way rather than relying upon the conventional methods which are used to estimate angles of arrival (DoAs) which are based on the two primary methods like MUltiple SIgnal Classification (MUSIC) algorithm and Estimation of Signal Parameters via Rational Invariance Techniques (ESPRIT) algorithm. Table I summarize the comparison of previous related work with our work. The subspace methods, such as ESPRIT and MUSIC, are popular techniques for DoA estimation in wireless communication systems. However, when the number of sources is large, these methods can face some disadvantages. The computational complexity of subspace methods grows rapidly with the number of sources, which can make these methods computationally expensive for large-scale antenna arrays [19–21]. Instead, we have used compressive sensing technique. In DoAs estimation based compressive sensing technique, it could take advantage of compressive sensing innovation to lower learning and feedback costs, as well as prior knowledge of the sparsity level, to further enhance prediction accuracy. CS-based DoA estimation can achieve the same level of accuracy with fewer sensors compared to traditional subspace DoA estimation techniques. This can lead to more cost-effective and compact sensing systems [22–24]. Traditional DoA estimation techniques require a uniform or linear array of sensors for accurate estimation. In contrast, CS-based DoA estimation is more robust to array geometry and can work with non-uniform or irregular arrays of sensors. CS-based DoA estimation can often achieve higher accuracy in low signal-to-noise ratio (SNR) environments compared to traditional subspace DoA estimation techniques. This is because CS can recover a sparse signal even when the measurements are highly corrupted by noise. Overall, DoA estimation using compressive sensing can lead to more efficient and accurate signal processing for many practical applications, especially in low-SNR and resource- constrained scenarios [25, 26].

The rest of this paper is organized as follows: Next section describes the system model. Following section introduces the proposed algorithm for DoA estimation based CS technique. Then, we presents the numerical results of the proposed algorithm. Finally, we discuss the results and conclude the paper.

TABLE I. A BRIEF REVIEW OF PREVIOUS RELATED WORK WITH OUR WORK

Ref.	System	Operation mode	Techniques	Objectives
Shen *et al.* [12]	Massive MIMO	FDD	Weighted l_1	Reduction in training overhead
Gao *et al.* [13]	Massive MIMO	FDD	CS	Reduction in training overhead
Almosa *et al.* [14]	Massive MIMO	FDD	CS	Reduction in training overhead
Kim and Shim [15]	Cell free Massive MIMO	FDD	Gradient descent	Improved the accuracy of CSI estimated
Almosa *et al.* [16]	Massive MIMO	FDD	ESPRIT	Improved the accuracy of CSI estimated
Our work	Cell free Massive MIMO	FDD	CS	Reduction in training overhead and improved the CSI estimated

II. SYSTEM MODEL

We adopt a CF massive MIMO network based on FDD with a centralized unit including M base stations, which has a uniform array structure with N antennas and K mobile station as shown in Fig. 1(b). The base stations and mobile stations have located in arbitrary manner within a coverage region. By transferring data system such as power control coefficients, precoding vectors and channel coefficients estimated, All base stations are linked with a centralized unit via backbone lines with unlimited resources and no errors.[1] In this work, scattered pattern for the wireless channel is taken into account, where it supposed that each scattering group contributes just one link. Taking into account a limited variety of easily solvable routes connecting the base station and the mobile station, the channel vector between m^{th} AP and k^{th} user can be represented as

$$\mathbf{g}_{mk} = \sum_{\ell=1}^{L} \sqrt{\beta_{mk_\ell}} h_{mk_\ell} \mathbf{a}(\theta_{mk_\ell}), \tag{2}$$

where L represents all the paths between the transmitter and the user, β_{mk_ℓ} models the fading coefficient, large-scale(LS) for the ℓ-th link of the channel takes link attenuation and shadow effects into consideration. LS coefficients in CF network varies in each couple of transmitter and receiver, in contrast to co-location network [7]. h_{mk_ℓ} represents small-scale fading coefficient for the ℓ-th path of the channel which are modeled as independent and identically distributed (i.i.d.) complex Gaussian variables with zero mean and unit variance. Thus, $h_{mk_\ell} \sim \mathcal{CN}(0,1)$. Furthermore, $\mathbf{a}(\theta_{mk_\ell}) \in \mathbb{C}^{N\times 1}$ represents the steering array vector for the ℓ-th link that lead from m^{th} AP to k^{th} user. It is evident that the steering vectors are affected by the transmitted direction of departure (DoD) in the downlink phase and DoA of the received signal in the uplink phase. By exploiting the reciprocity property between uplink and downlink phases [17], we developed efficient algorithm for DoAs estimation based on CS technique. In addition, we consider that LS coefficients are same for both directions due to independency on frequency. However, small scale channel coefficients are different between uplink and downlink direction because they are function of frequency. For the AP equipped with a uniform array structure, the steering vector can be expressed using the Vandermonde structure: $\mathbf{a}(\theta_\ell) = [1 \quad e^{j\omega_\ell} \quad \dots \quad e^{j(N-1)\omega_\ell}]^T$, where $\omega_\ell = (2\pi d/\lambda)\cos\theta_\ell$, d is the space that seperates the neighboring elements of antenna, λ is the carrier wavelength, and θ_ℓ is the DoA and DoD related to the ℓ-th link of the UL and DL channel, respectively. We also consider a coherence block model in which channel prediction and its feedback methods treat small scale coefficients as fixed across a limited number of time frames. In the same way, we suppose that LS coefficients remain fixed during LS coherence intervals. Different coherence intervals for both small and large coefficients are taken to be unrelated. In this work, we consider frequency-division duplexing (FDD) operation mode, where the dominant channel direction is same between uplink and downlink transmission. The channel vector in Eq. (3) can be written in compact form as:

$$\begin{aligned} \mathbf{g}_{mk} &= \mathbf{A}_{mk}\mathbf{D}_{mk}\mathbf{s}_{mk} \\ \mathbf{A}_{mk} &= [\mathbf{a}(\theta_{mk_1}) \dots \mathbf{a}(\theta_{mk_\ell}) \dots \mathbf{a}(\theta_{mk_L})] \\ \mathbf{D}_{mk} &= \mathrm{diag}\left(\sqrt{\beta_{mk_1}} \dots \sqrt{\beta_{mk_\ell}} \dots \sqrt{\beta_{mk_L}}\right) \\ \mathbf{s}_{mk} &= [h_{mk_1} \dots h_{mk_\ell} \dots h_{mk_L}]^T \end{aligned} \tag{3}$$

where $\mathbf{A}_{mk} \in \mathbb{C}^{N\times L}$ is the array steering matrix, which contains information about the uplink directions (DoAs) for the all paths of k^{th} user, $\mathbf{D}_{mk} \in \mathbb{C}^{L\times L}$ is the diagonal matrix contains the large-scale fading coefficients for the all paths of k^{th} user's channel, and $\mathbf{s}_{mk} \in \mathbb{C}^{L\times 1}$ is the small-scale fading coefficients vector.

III. PROPOSED ALGORITHM FOR DOA ESTIMATION BASED CS

CS is a technique that can be used to estimate theDoA of signals in a cell-free massive MIMO systems. In a cell-

[1] However, in a realistic situation, the backbone lines linkages are subject to restrictions, and examining the impact of these limitations would be a significant area of research for the next generations.

free massive MIMO systems, a large number of APs are distributed over a wide area to provide coverage and capacity. The DoA estimation problem in this scenario is to determine the angles of arrival of signals from multiple users at each AP. CS can be used to solve this problem through utilizing the UL sparsity property related to the uplink channel matrix, where only a small number of paths are active at a time. In CS, a measurement matrix is designed to capture the sparse nature of the problem, and the DoA estimation are obtained by solving an optimization problem [27]. The proposed algorithm has been shown to have better performance in terms of accuracy. The estimation of DoAs for each user is done through uplink training phase as follow. First, all users simultaneously and synchronously send pilot sequences $\boldsymbol{\psi}_1, \dots, \boldsymbol{\psi}_K \in \mathbb{C}^{1\times\tau}$ to all APs , where τ denotes the length of pilot sequence for each user. At the next step of this process, each AP estimates the channel directions along with the LS multipath components related to all users based on the received pilot signals and use these estimates to precode and beamform the message intended for each user. We assume low user mobility and hence the pilot contamination can be neglected. We consider all training signals with duration $\tau \geq K$ are mutually orthonormal, $\boldsymbol{\psi}_j^H \boldsymbol{\psi}_i = \delta(j-i)$, where δ is Dirac delta function. The received signal $\mathbf{Y}_m \in \mathbb{C}^{N\times\tau}$ at the m^{th} AP during uplink training phase can be written as:

$$\mathbf{Y}_m = \sqrt{\rho_u} \sum_{k=1}^{K} \mathbf{g}_{mk} \boldsymbol{\psi}_k + \mathbf{N}_m, \quad (4)$$

where ρ_u is maximum uplink power transmitted by each user and $\mathbf{N}_m \sim \mathcal{CN}(0, \sigma_n^2 I_N)$ is additive Gaussian noise. By multiplying Eq. (4) by $\boldsymbol{\psi}_k^H$, we get the received signal for k^{th} user as follow:

$$\mathbf{Y}_m \boldsymbol{\psi}_k^H = \sqrt{\rho_u} \mathbf{g}_{mk} + \mathbf{N}_m \boldsymbol{\psi}_k^H, \quad (5)$$

let $\mathbf{y}_{mk} = \mathbf{Y}_m \boldsymbol{\psi}_k^H \in \mathbb{C}^{N\times 1}$ and $\mathbf{n}_{mk} = \mathbf{N}_m \boldsymbol{\psi}_k^H \in \mathbb{C}^{N\times 1}$, then the received signal for k^{th} user can be written as:

$$\mathbf{y}_{mk} = \sqrt{\rho_u} \mathbf{g}_{mk} + \mathbf{n}_{mk}, \quad (6)$$

By substituting Eq. (3–6), we get:

$$\mathbf{y}_{mk} = \sqrt{\rho_u} \mathbf{A}_{mk} \mathbf{D}_{mk} \mathbf{s}_{mk} + \mathbf{n}_{mk}, \quad (7)$$

let $\mathbf{x}_{mk} = \mathbf{D}_{mk} \mathbf{s}_{mk} \in \mathbb{C}^{L\times 1}$, then Eq. (7) can be rewritten as:

$$\mathbf{y}_{mk} = \sqrt{\rho_u} \mathbf{A}_{mk} \mathbf{x}_{mk} + \mathbf{n}_{mk}, \quad (8)$$

a sparse signal can be recovered using the signal processing method known as CS from a sparse set of observations [23]. DoAs estimation is one of the applications where CS can be used to lower the amount of observations needed to estimate the DoAs of multiple signals. In DoAs estimation using CS, the goal is to estimate the directions of arrival of signals using a small number of measurements from a sparse array of sensors. The sparse array has fewer sensors than the number of sources and the sources are assumed to be sparse or concentrated in a small number of directions. The measurement model can be represented as:

$$\mathbf{y} = \sqrt{\rho_u} \mathbf{A}\mathbf{x} + \mathbf{n}, \quad (9)$$

where the subscript is omitted for simplicity, $\mathbf{y} \in \mathbb{C}^{N\times 1}$is the measurement vector, $\mathbf{A} \in \mathbb{C}^{N\times P}$ is the sensing matrix, where P is the angle grid. Fig. 2 shows the block diagram of DoA estimation based CS. The sensing matrix is a key component of the measurement process that maps a high-dimensional signal to a low-dimensional measurement space. The sensing matrix is typically designed to enable the recovery of the original signal from a small number of measurements. The entries of the sensing matrix are typically random, but can also be carefully designed to have certain properties that enable efficient and accurate signal recovery [22]. One common approach for designing the measurement matrix is to use a Gaussian or Bernoulli random matrix, where the entries are chosen from Bernoulli or Gaussian distribution, respectively. These types of random matrices have been shown to work well for many types of signals and can enable efficient signal recovery using algorithms such as basis pursuit, orthogonal matching pursuit, and others. Other types of sensing matrices that can be used in compressive sensing include structured matrices as in our case such as Fourier and wavelet matrices, which are often useful for signals with sparse or compressible representations in those domains [22, 25]. In general, the choice of sensing matrix can have a significant impact on the accuracy and efficiency of the signal recovery process in compressive sensing. The measurement matrix $\mathbf{A}$ is typically constructed so that it is incoherent with the sparsity signal represented by the vector $\mathbf{x}$, which means that the projection of $\mathbf{x}$ onto $\mathbf{A}$ is random and non-redundant. $\mathbf{x} \in \mathbb{C}^P$ is the sparse signal vector. The strongest column's index related to the measurement matrix must be chosen in order for the traditional CS method to function properly. The CS literature states that for some random matrices, there is a substantial likelihood that the traditional method will not choose the right column during the initial iteration [23]. In order to solve this problem, a proposed algorithm to acquire the estimated DoAs is developed in this study. As we are interested in DoAs estimation in our scenario and the proposed algorithm relies on the objective functions, we select linear model as optimization problem. The proposed algorithm refreshes the feature set after each iteration by picking the top features related to the sensing matrix depending on the cost function. The algorithm iteratively adds the index of the column of $\boldsymbol{A}$ with the largest inner product with the current residual to the support set S. It then solves a least squares problem over the columns of $\boldsymbol{A}$ indexed by S to obtain the coefficients for the sparse solution. The residual is updated and the process is repeated until L iterations have been completed. The final output is the DoAs corresponding to the index of nonzero elements in the sparse solution $\widehat{\boldsymbol{x}}_S$. Algorithm 1 provides a summary of the suggested approach. The covariance matrix of $\mathbf{x}$ in Eq. (9) can be written as:

$$\mathbf{X} = \mathbb{E}[\mathbf{x}\mathbf{x}^H] = \mathbb{E}[\mathbf{D}\mathbf{s}\mathbf{s}^H\mathbf{D}^H] = \mathbf{D}\mathbf{D}^H = \text{diag}[\beta_1 \ldots \beta_L], \tag{10}$$

After estimated the array steering matrix from previous step, the estimated of covariance matrix can be computed as follow:

$$\widehat{\mathbf{X}} = \hat{\mathbf{x}}\hat{\mathbf{x}}^H, \tag{11}$$

where $\hat{\mathbf{x}} = \frac{1}{\sqrt{\rho_u}}(\widehat{\mathbf{A}}^{\mathbf{H}}\widehat{\mathbf{A}})^{-1}\widehat{\mathbf{A}}^{\mathbf{H}}\mathbf{y}$ and the estimated of LS coefficients is given by:

$$\widehat{\boldsymbol{\beta}} = \text{diag}[\widehat{\mathbf{X}}] = [\beta_1 \ldots \beta_L] \tag{12}$$

Algorithm 1. Proposed algorithm for DoAs estimation based on CS technique

Input: $\boldsymbol{y}, \boldsymbol{A}, P, and\ L$
Start: $\boldsymbol{r} = \boldsymbol{y}, S = [\,]$
While $j \leq L$
Calculate the inner products between the residual and columns of **A**: $\text{abs}(\boldsymbol{A}^{\boldsymbol{T}}\mathbf{r})$
Find the index of the largest inner product: $k = argmax\ |\text{abs}(\boldsymbol{A}^{\boldsymbol{T}}\mathbf{r})|$
Add the index to the support set: $S = [S, k]$
Solve the least squares problem: $\widehat{\boldsymbol{x}}_S = \boldsymbol{A}_S{}^{\dagger}\boldsymbol{y}$
Update the residual: $\boldsymbol{r} = \boldsymbol{y} - \boldsymbol{A}_S\widehat{\boldsymbol{x}}_S$
End
Output: DoAs corresponding to L paths

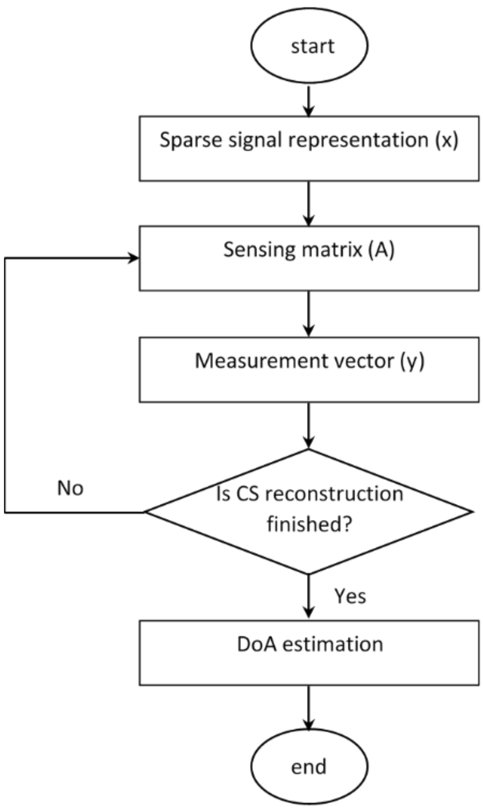


Figure 2. Block diagram of DoA estimation based CS.

IV. Result and Discussion

The effectiveness of the proposed algorithm is evaluated in this section. We examine a square area with a side length of 1 km, where K single antenna users and M APs, each with N antennas are distributed randomly. The antenna spacing for transmit antennas is considered as 0.5λ. It is believed that the edges are wrapped around in order to prevent edge effect. The COST Hata concept is utilized for LS coefficients , which can provide important information about the system's performance in terms of coverage, capacity, and data rate. The COST Hata model is a widely used empirical model for the prediction of radio wave propagation in urban, suburban, and rural environments. By considering the large-scale fading coefficients, we can gain insight into how the radio wave propagation affects the overall system performance. Table II contains all of the system parameters. The COST Hata model can be written as [7]

$$\log_{\mathbf{10}}(\beta_{mk}) = -13.6 - 3.5 \log_{\mathbf{10}}(d_{mk}) + \frac{Z_{mk}}{10} \tag{13}$$

where $Z_{mk} \sim \mathcal{N}(0, \sigma^2_{\text{shadowing}})$ and d_{mk} is the distance between user, k and access point, m in kilometres. We consider normalized transmitted SNR in all calculations, where transmit SNR can be calculated by dividing transmit power by the noise variance, which is given by [7]

$$\text{noise variance at receiver} = NF \times \kappa \times B \times T \tag{14}$$

where κ is the Boltzmann constant, T is temperature in Kelvin, B is the bandwidth in Hz, and NF is the noise figure in Watt. Numerical results are presented in this part to assess the performance of CF system based FDD with the proposed algorithm. For comparison with traditional DoAs estimation method, We examine two different situations. The first scenario assumed that the number of the propagation paths for the channel between user k and AP m to be two. The number of paths for channel in the second case is considered as three. As evaluation criteria, we considered Root Mean Square Error (RMSE) to investigate the quality of the proposed DoAs estimation method based CS discussued in previous section with the traditional DoAs estimation subspace method, ESPRIT. We consider ESPRIT algorithm for comparison because the ESPRIT algorithm provides high accuracy in the estimation of the DoAs, even in the presence of noise and interference. In addition, the ESPRIT algorithm is robust to uncertainties in the signal model, such as the presence of multipath signals or spatial correlations between the signals.

Fig. 3 shows the average RMSE of the proposed algorithm versus SNR with two paths for the channel between AP m and user k. It is obivious that our proposed algorithm outperforms the traditional method, which is subspace method based on the rotational invariance property of the eigenvectors of a covariance matrix derived from the received signals. It is clear that as the SNR increased, the performance of the proposed algorithm becomes more accurate compared with the traditional method because our algorithm exploits the sparse nature of the DoA estimation problem, where only a small number of paths are active at a time. In CS, a measurement matrix is designed to capture the sparse nature of the problem, and the DoA estimates are obtained by solving an optimization problem.

Fig. 4 shows the average RMSE of the suggested algorithm against SNR for N = 32, K = 8 with three paths for the channel between AP $\boldsymbol{m}$ and user $\boldsymbol{k}$. We observe that ESPRIT algorithm still has poor performane compared with the proposed algorithm due to large number of antennas at AP. However, the suggested method outperforms the conventional DoAs estimation method since it takes use of the uplink channel matrix's sparse topology and as the sparsity level increase, the performance of the algorithm will decrease, which is a common feature of the greedy CS algorithm.

Fig. 5 shows the average RMSE of the suggested algorithm against training length for N = 32, K = 8 with three paths for the channel between AP $\boldsymbol{m}$ and user $\boldsymbol{k}$. It is clear that our proposed algorithm based CS can achieve an accurate estimation of DoAs with much lower training overhead compared with traditional subspace method. In Fig. 5, we observe that ESPRIT method can achieve $\mathbf{10^{-2}}$ with training length around 70. However, our proposed algorithm can achieve $\mathbf{5 \times 10^{-3}}$ with training length around 10. Thus, our algorithm achieve an efficient reduction in training overhead.

TABLE II. SIMULATION SYSTEM PARAMETERS

Parameter	Value
M	64
N	32
K	8
d	0.5λ
$T_{\circ}$	290 Kelvin
B	10 MHz
NF	9 dB
$\sigma_{\text{shadowing}}$	8 dB
uplink power ρ_{ul}	200 mW
carrier frequency for uplink channel	49.8 GHz
carrier frequency for downlink channel	50 GHz
coherence bandwidth	200 KHz
coherence time	1 ms
length of pilot training τ	K
angle spread	15°

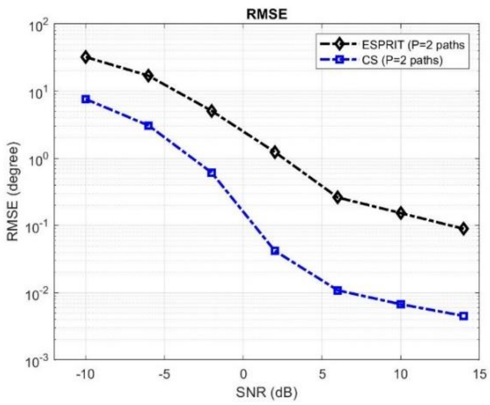


Figure 3. Average RMSE of the proposed algorithm against SNR for K= 8, N = 32, and two paths for the channel.

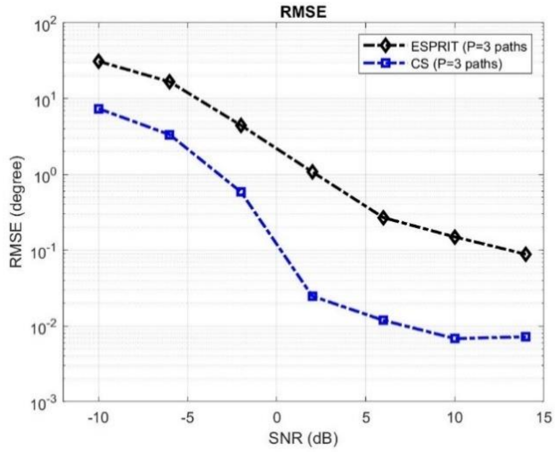


Figure 4. Average RMSE of the proposed algorithm versus SNR for N = 32, K = 8, and three paths for the channel.

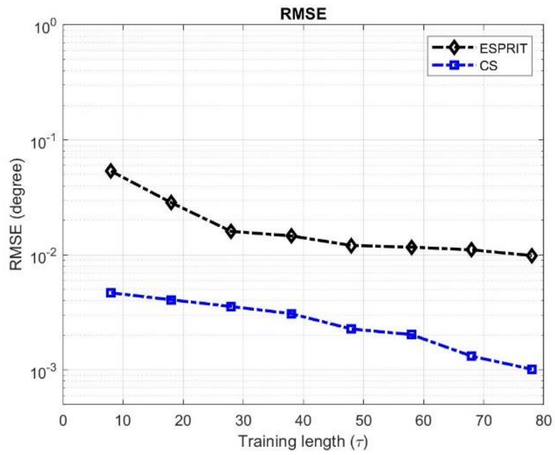


Figure 5. Average RMSE of the proposed algorithm versus training length for N = 32, K = 8, and three paths for the channel.

V. CONCLUSION

In this paper, the used approach has been demonstrated to have better performance in terms of accuracy. The estimation of DoAs for each user is done through uplink training side as shown. Each AP estimates the channel directions along with the LS coefficients to all users based on the received pilot signals and use these estimates to precode and beamform the message intended for each user. We assume low user mobility and hence the pilot contamination is negligible. The benefit of DoA estimation in FDD system for cell-free massive MIMO systems is to improve the performance of the wireless communication system by providing more accurate information on the direction from which signals are arriving at the receiver. The performance evaluation of FDD cell free massive MIMO systems with the proposed algorithm has been done in respect to the comparison with traditional DoAs estimation method, our estimation is based upon two assumptions, firstly the propagation paths of the channel between a user and an AP are only two. The number of paths for the channel in the second case is considered as three. We used RMSE as a benchmark to assess how well the suggested DoAs estimation approach based on compressive sensing performed. In both cases, the results demonstrated that the suggested algorithm performed significantly better in terms of accuracy in real-world environments than the conventional DoA subspace methods.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

H. A. developed the theory and formulated the problem, performed the analytic calculations and performed the numerical simulations. Y. H. analyzed the results. M. A. wrote the paper. A. B. supervised the project. All authors had approved the final version.

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