AP selection in Cell-Free Massive MIMO system using Machine Learning Algorithm

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***Abstract*—Current cellular networks work by creating autonomous cells that fail to serve many users due to uneven coverage area. With the world becoming more reliant on the wireless communication system, a cellular network with multiple wireless access points, high spectral and energy efficiency is a must. These requirements are fulfilled by a cell-free Massive multiple-input multiple-output (MIMO) network. Apart from being ideal for the current wireless communication's requirements, it can also resolve a lot of currently faced interference issues. With this work, we aim to reduce the complexity so this system becomes more practical to deploy in the real world and reduce one of the limitations of a cell free massive MIMO system. We propose a new access point selection algorithm called CAPS (Cluster based AP selection) for the cell-free Massive MIMO which is aimed at reducing the computations workload and pilot contamination by introducing machine learning algorithm for clustering which in our work is the K-means++ clustering algorithm. The simulations and calculations show that using the proposed algorithm have performed better compared to prevailing approaches.**

Keywords—Cell free Massive MIMO, Antenna. Access point, AP selection, Machine learning, K-means clustering

I. Introduction

A massive multiple-input multiple-output is one of the most promising wireless communication systems. The system comprises of an extensive number of antennas which are equipped on a large number of service antennas referred to as the access points (AP). This system can be more relied upon in comparison to the current cellular network and serves multiple users in the same time-frequency resource with a higher throughput [1,2]. The extensive number of antennas prove to be extremely beneficial in the removal of noise and interference from user equipments (UE) [3]. In contrast to Massive MIMO, the concept of Cell-free Massive MIMO is more practical and efficient for wireless access technology. It procures all the major benefits from the concepts of distributed MIMO and Massive MIMO such as provision for a uniform good service for all users in the network, higher spectral and energy efficiency and simple signal processing [5]. In distributed MIMO, the antennas are scattered over a vast region giving the system the potential to cover a larger area than Massive MIMO [4]. As the name suggests a Cell-free massive MIMO has no cells or cell boundaries. It comprises a very vast number of access points (AP) and a comparatively smaller number of active user equipment (UE) distributed over a vast area. The access points use directly the measured channel characteristics to jointly serve all users in the same time-frequency band. This means that numerous single-antenna APs can serve a comparatively smaller number of user equipments simultaneously. For this work, we will be considering a conventional cell free Massive MIMO in time-division duplex (TDD) operation with M access points and K user equipment where all the M APs are connected to a central processing unit via the backhaul network. The CPU executes the necessary computation for network synchronization though it is to be noted that the exchange of channel state information (CSI) among the various APs and the CPU is depended upon the payload data hence there is no provision for fast communication of CSI between the APs and the CPU [5]. This, in turn, delays in the assignment of antennas serving to the UEs with the added issue of pilot contamination effect. Along with this, the cell-free Massive MIMO system provides us these benefits at the cost of added advanced hardware for dealing with the computational intricacies for the pilot assignment and power control.

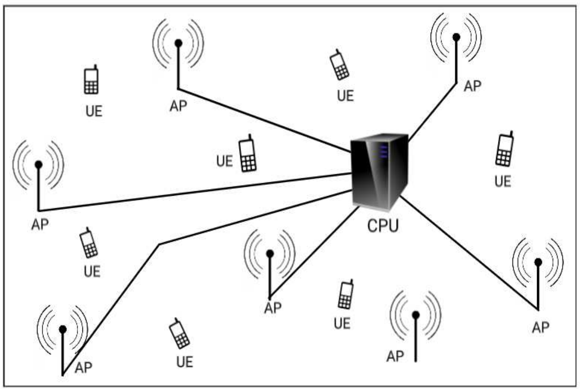

Fig. 1. System model of cell-free Massive MIMO system

To deal with these complexities, the antenna selection algorithm in [6,7] is acquired from the square max volume submatrices scheme, in which the number of the selected transmitting antennas is equal to the number of users. In other antenna selection algorithms, generally, algorithms are based upon channel capacity [8] or custom threshold based on signal-to-noise ratio (SNR) at the receiver [9-11]. Though these algorithms are effective in producing a pilot antenna sequence, they generate a lot of computational load on the CPU. The proposed algorithm called Cluster AP Selection (CAPS) Algorithm uses clustering machine learning algorithms to accelerate the AP assignment and further reducing probable pilot contamination.

The paper is structured as so; In section 2, we discuss the adopted system model for the CAPS Algorithm along with the algorithm design. In section 3, we study the simulations and the numerical results and in section 4, we conclude the paper.

II. SYSTEM MODEL

For a Cell-Free Massive MIMO system with M APs and K user equipment in TDD which means that the uplink and downlink channels are reciprocal of each other, where $M >> K$. These APs are geographically distributed serving all the K users. Initially, all user equipments and APs are allocated a single antenna randomly in the vast area along with the assumption that all APs are randomly located throughout the area and are assumed to have perfect CSI.

We denote g_{mk} as the channel between the m_{th} AP and the k_{th} UE. The channel g_{mk} models large-scale fading β_{mk} and small-scale fading h_{mk} as:

$$g_{mk} = \sqrt{\beta_{mk}} h_{mk} \tag{1}$$

In TDD mode, there are three activities within coherence intervals; the uplink training, downlink data transmission, and uplink data transmission. The uplink data transmission deals with the channel estimations of all K users. In this work we will focus on downlink payload data transmission

Research methodology applied in this article involves proposing a clustering algorithm for optimal selection of access point with improved spectral efficiency for cell free massive MIMO system. It also involved training and channel estimation for aid of the AP selection.

The proposed clustering algorithm is simulated under cell free massive MIMO system using K-means++ clustering algorithm which is tailored for AP selection problem.

A. Training and Channel Estimation

The uplink training and channel estimation is done via the transmission of the pilot sequence from all user equipments to all the access points in the network. The estimation for the channels is done using the linear minimum mean square error. At this stage, there is a chance of pilot contamination. Like in [1], 200 is estimated to be the maximum number of pilot sequences in a one millisecond coherence interval. The available orthogonal pilot sequences are thus easily exhausted in a system like this.

B. Downlink Data Transmission

After the training and channel estimation from all K UEs to all M APs, the data is ready to be transmitted. It's assumed that every UE in the network is connected to one AP and every AP can serve multiple UEs simultaneously. The signal which is being transmitted by the K^{th} AP to serve a set of U_k users is given by

$$s_k = \sum \sqrt{p_d} \mathbf{w}_{kl} d_k \tag{2}$$

where p_d denotes the transmit data power common for all users and d_k denotes the transmitted data for the k_{th} user with $E\{|d_k|^2\} = 1$

C. AP selection model

In this section, we model the K-means++ clustering algorithm along with the metrics to assign the AP to the user. The metrics are based on the closed-form of spectral efficiency which is derived in [13] based on the assumption that τ_c is the time duration of each coherent interval, τ_p is utilized for pilot uplink transmission and $(\tau_c - \tau_p)$ is the remaining time duration for the downlink data transmission.

$$S_k = \frac{\tau_c - \tau_p}{\tau_c} \log\left(1 + \frac{M^2 p_d \eta_{kl}^2}{\sum_{j=1}^{L} \sum_{t=1}^{|U_j|} M p_d \eta_{tj} \beta_{kj} + 1}\right). \tag{3}$$

where S_k is the closed form spectral efficiency for the k^{th} user. We model the K-means clustering create suitable clusters of all APs present in the network of geographical space. These clusters unlike the current cellular network are optimally classified into Voronoi cells using the squared Euclidean distances without the constraints of a non-Massive MIMO system and issues with edge of a cellular network [5]. The algorithm doesn't create harsh geographical cells which serve issues when near the edges of the cells but creates dynamic clusters based on the number of users in the network at a current point in time τ_i.

For each user equipment U_i with a pilot sequence from the training and channel estimation period, a subset H_i of APs will be created. The sequence of APs ready to serve the user equipment U_i will be given by using the subset H_i and calculating the Spectral efficiency (SE) as in (3). The APs with the highest values of SE are chosen for that particular user.

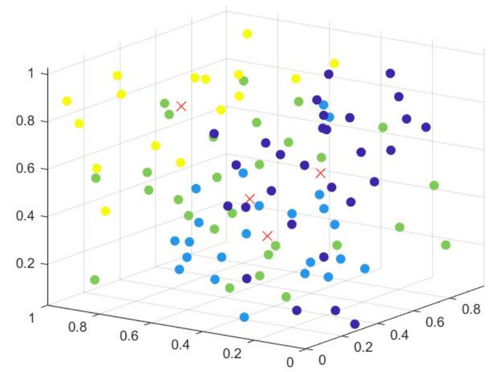

Fig. 2. Access Point clustering using K-means++ Algorithm

Algorithm: CAPS - Cluster based Access point Selection Algorithm

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Initialize: Initial number of clusters C and pilot sequence set H_i serving each user.

1. Calculate the distance X_i from all existing clusters' centroid $\forall i = 1, 2 \ldots K$
2. Sort X_i in ascending order and assign the first cluster to UE U_i $\forall i = 1, 2 \ldots K$
3. Create a subset M_i for all APs present in common with the cluster and the pilot sequence.
4. Calculate the SE as in (3) for set M_i to acquire the APs available to UE U_i $\forall i = 1, 2 \ldots K$
5. Sort M_i based on the SE in ascending order and assign the AP on top to U_i at a point of time
6. Run the algorithm from step 2 till all users have been assigned to an AP.

For each user, we select the first AP from the sorted list M_i where M_i is the available list of APs for the particular user within the cluster. The algorithm can be invoked on relocation. Based on the number of UEs in the network, the clusters could be increased or decreased which is further discussed in Section IV. For UEs extremely close to each other geographically, Step 5 and 6 guarantees that every UE will be assigned the most suitable AP and not just the AP with the highest channel gain or large-scale fading coefficient.

For validation, we check the large-scale fading coefficient.

$$\beta_{kl} = -35.3 - \gamma \log_{10}(d_{kl}) + z_{kl}, \tag{4}$$

In (4), if β_{kl} is large, the assigned channel quality from the user equipment U_i to assigned K_i AP is good [13].

The CAPS algorithm is based on heuristic observations due to which it has extremely low complexity compared to other algorithm [13-15].

III. Numerical Analysis

We will be analyzing the performance of the CAPS algorithm by comparing it to other AP selection algorithms - random AP assignment, fully connected network AP assignment and large-scale fading coefficient-based AP assignment [15].

Table 1 provides simulation parameters utilized for the system simulation of this research. For simulation, cellular communication in area of $1km^2$ is taken under consideration. For MIMO system, base station antenna of 100 is considered with the assumption of each AP has 5 antenna and no. of users are 10. This is assumed to provide more spatial degree of freedom at base station.

Typical 20Mhz bandwidth is assumed because cellular system is operating with multiple of 20Mhz bandwidth. The system is operated under low power mode with 20mW power. This low power transmission is assumed to access the capability of the proposed algorithm under low power transmit mode.

TABLE I. Simulation Parameters of the system

Parameters	**Values**
Area	$1KM^2$
No. of APs (L)	5
No. of Users (K)	10
No. of antenna (M)	100
Bandwidth	20Mhz
Pilot & data power	200mW

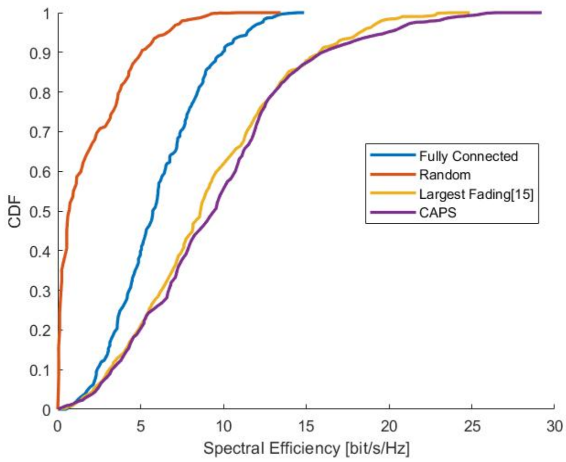

Fig. 3. CDF of the system sum rate with L=5, K=10,M=100

A. Comparitive Study

In order to access the capacity of the posed mechanism, Cumulative distribution of the system is computed for 4 cases.

Case 1: Random AP selection mechanism – The user equipments and the antennas are randomly assigned to each other irrespective of the channel quality or any other metric. On plotting the CDF for the all the assignments, we can see that random assignment has performed extremely poorly and isn't a good choice for real life implementation. Case 2: Fully Connected System – In this network all UEs are connected to all APs in the network. Not only is it a waste of resources but it doesn't outperform the other algorithms in consideration except random assignment which is the baseline.

Case 3: Largest Fading Coefficient - An AP selection algorithm based on large scale fading [15] given under the name 'Largest Fading' in figure 3. In this approach the UE is connected to the AP having the maximum large scale fading coefficient.

Case 4: CAPS - Fig. 3 shows that CAPS Algorithm out performs the considered algorithms. CAPS out performs the largest fading algorithm [15] by 2.23 bit/s/Hz at 0.97 probability for the system parameters given in table 1. The graph shows that the proposed system will scale up comparatively better as well.

Additionally, CAPS algorithm is computationally lighter than any of the considering algorithms as shown in Table 2 where N is the total number of antennas, and K is the number of clusters for the APs.

TABLE II. Computational complexity for the algorithms

CAPS	Random	Fully Connected	Largest Fading
O(NK)	O(1)	$O(N^N)$	$O(N^N)$

From Table II and figure 3, we compare and arrive at an optimal balance between computational workload for the CPU of a cell free Massive MIMO and the performance of the algorithm. We can observe that with the computational workload pulled up by CAPS, the algorithm is out performing all the algorithms.

Table 2 clearly indicate the use of machine learning technique (MLT) and its's advantage that is it has it has very low computational complexity. From Fig 3, we can also observe that the proposed MLT technique outperforms existing techniques.

IV. Conclusion

In this paper, we have proposed a new algorithm Cluster based Access Based Selection Algorithm (CAPS) which is based on K-means++ algorithm for access point selection in cell free massive MIMO system. The immense number of computations at the CPU due to the architecture of the system imposed a huge problem in implementation of the system in real life. CAPS algorithm reduces the complexity without severing with the performance of the system by exploiting the K-means++ algorithm.

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