UNSUPERVISED USER CLUSTERING IN NON-ORTHOGONAL MULTIPLE ACCESS

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ABSTRACT

Non-orthogonal multiple access (NOMA) is one of the most promising technologies in fifth-generation mobile communication system for its advantages in serving multiuser simultaneously and enhancing spectrum efficiency. In this paper, we investigate the optimization problem of sum-rate maximization for NOMA-based system, and mainly focus on user clustering. Inspired by the correlation features of users, we introduce machine learning in user clustering. We first develop an expectation maximization (EM) based algorithm for fixed user scenario. Then, the dynamic user scenario is considered and an online EM (OLEM) based clustering algorithm is proposed. Simulation results show that the proposed EM-based and OLEM-based algorithms outperform the state-of-the-art algorithms in fixed and dynamic user scenario, respectively.

***Index Terms*—** NOMA, user clustering, unsupervised learning, expectation maximization, online learning

1. INTRODUCTION

With the rapid increase of mobile-connected devices, fifth-generation (5G) is developed to enable higher user density, lower latency, and higher spectrum efficiency [1, 2]. Since the traditional multiple access (MA) technology in fourth-generation (4G) has a limitation on supporting a moderate number of active devices simultaneously [3], new MA technologies are expected in 5G, such as the power domain non-orthogonal multiple access (NOMA) [4]. Utilize the non-orthogonality in power domain, the NOMA-based system can share resources among users within one resource block (RB), and improve the performance of the system [5]. In that case, the user association of each RB is crucial for the optimization problem in the NOMA-based system [6].

Generally, the NOMA-based system is implemented by a hybrid multiple access technology that integrates the NOMA technology for each beam and orthogonal multiple access (OMA) technology for different beams, such as NOMA combined orthogonal frequency-division multiple access (OFDMA) [7]. The users in the same beam have strong channel correlation, while users in different beams have little correlation [8]. Therefore, the procedure of dividing users into different beams is equal to cluster the users by exploiting some features of users, and make sure that users in the same cluster are alike, but distinct in different clusters. In [9], the authors studied the impact of user pairing on the performance of two NOMA systems, i.e., NOMA with fixed power allocation and cognitive-radio-inspired NOMA. The authors in [10] investigated the effects of near-far user pairing on the performance of cell center, mid, and edge users, and two user pairing strategies were proposed for accommodating all the users. In [11], the authors proposed a channel status sorting pairing algorithm for user pairing and the user difference selecting access algorithm for new users to access. In [12], the authors proposed a cluster-head-based user clustering algorithm, which exploits the channel gain differences and correlations among NOMA users. In addition, the design of the beamformer is also important for the NOMA-based system, and the methods for beamforming were studied in [13, 14].

Since the performance of clustering depends on the feature space, it is important to describe the users in a proper feature space and select the algorithm based on the properties of the feature space. The conventional user clustering algorithms mostly rely on some statistical methods, but rarely consider the user distribution of each cluster. On the other hand, these methods can only be used in fixed user scenario, unsuitable in dynamic user scenario. Inspired by the characteristics of unsupervised machine learning that can induce the latent structures from raw data [15,16], in this paper, we apply the unsupervised learning to learn the inherent structures and correlationships of users, and propose the unsupervised learning based user clustering methods, both for fixed and dynamic user scenarios.

2. SYSTEM MODEL

In this section, we consider a downlink NOMA-based mobile cellular model, which consists of one base station (BS) equipped with M antennas and N users with a single-antenna. The users can be divided into K clusters, and then NOMA can be applied to each cluster for the purpose of serving multiuser simultaneously. Specifically, we consider both the fixed user scenario and the dynamic user scenario.

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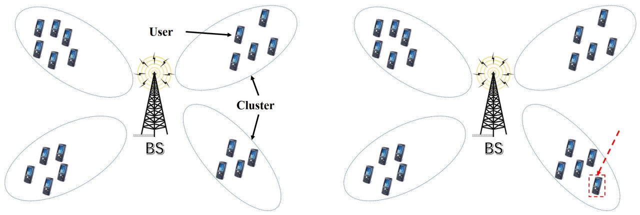


(a) Fixed User Scenario (b) Dynamic User Scenario

Fig. 1. Illustration of the NOMA-based downlink cellular model, including the fixed user scenario and dynamic user scenario.

2.1. Fixed user scenario

First, we initialize the basic NOMA-based downlink cellular system. We focus on the scenario of a small area, in which the users are physically clustered [17]. For illustrative purposes, we construct the model in a 2D plane. The illustration of the NOMA-based fixed user scenario is shown in Fig.1(a). The construction of the model consists of the following three parts.

User Distribution Model: Inspired by the real physically clustered users, we focus on a correlated setup in which users lie closer to form the clusters [17]. Given a cluster center, the users of this cluster are independently identically distributed (i.i.d.) and generated by the density $F_k(u)$, expressed as

$$F_k(u) = \frac{1}{2\pi\sigma_k^2} exp(-\frac{||u||^2}{2\sigma_k^2}), k = 1, 2...K, \tag{1}$$

where σ_k^2 is the variance and K is the number of clusters.

Channel Model: As discussed in [18], the channels are expected to have limited scattering, which are expressed as

$$H_u = \sqrt{\frac{M}{\rho}} \sum_{l=1}^{L} \alpha_l \boldsymbol{a}_{AoD}(\theta_{u,l}) \boldsymbol{a}_{AoA}(\phi_{u,l}), \tag{2}$$

where ρ is the average path-loss between the BS and user. L is the number of total paths from the BS to the user, and α_l is the complex gain of the l^{th} path. The variables $\theta_{u,l}, \phi_{u,l} \in [0, 2\pi]$ are the azimuth of departure (AoD) and arrival (AoA) of the l^{th} path, respectively. $\boldsymbol{a}_{AoD}(\theta_{u,l})$ and $\boldsymbol{a}_{AoA}(\phi_{u,l})$ are the corresponding antenna array response vectors.

Signal Model: The users in cluster k are denoted as $u_{k,i}(k = 1, ..., K; i = 1, 2, ..., N_k)$, where N_k is the number of users in cluster k. The message sent to user $u_{k,i}$ is denoted as $s_{k,i}$. The superposition messages sent to cluster k are $X_k = \sum_{i=1}^{N_k} \sqrt{\beta_{k,i}} s_{k,i}$, where $\beta_{k,i}$ is the power splitting factor for users in cluster k. Therefore, the received signal at user $u_{k,i}$ can be expressed as

$$y_{k,i} = \boldsymbol{H}_{k,i} X_k + n_{k,i}, \tag{3}$$

where $\boldsymbol{H}_{k,i}$ is the channel gain between the BS and user $u_{k,i}$, and $n_{k,i}$ is the white Gaussian noise for user $u_{k,i}$.

2.2. Dynamic user scenario

In the real NOMA-based system, new users keep arriving and changing the user distribution of the clusters. In this case, we construct the dynamic user scenario by generating new users and moving them into the coverage of the BS. Suppose that a new user u_{k,N_k+1} moves into the NOMA-based system, where k is the cluster index that the user randomly moves in, and N_k is the number of users in cluster k at a previous time. The location of the new user is generated by the density of the user distribution model, which is sampled randomly around the cluster center with the density $F_k(u)$ and i.i.d. with the existed users. The dynamic user scenario is shown in Fig.1(b).

3. UNSUPERVISED MACHINE LEARNING-BASED USER CLUSTERING

In this section, we propose our unsupervised machine learning based user clustering methods, including an EM-based method for the fixed user scenario, and an online EM-based method for the dynamic user scenario.

3.1. EM-based method for the fixed user scenario

Since the BS can perceive the user state information, we denote the user set as $\boldsymbol{U} = \{\boldsymbol{u}_1, \boldsymbol{u}_2, ..., \boldsymbol{u}_N\}$, where N is the number of users and $\boldsymbol{u}_n$ is the user state. These users are physically clustered into K clusters, and the parameters of each cluster are $\boldsymbol{\theta}_k = \{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \omega_k\}$, where $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ are the mean and covariance matrix of cluster k, ω_k is the weight of each cluster. The distribution of all the users can be regarded as a Gaussian mixture distribution, which is written as a linear superposition of Gaussians [19]

$$p(\boldsymbol{U}) = \sum_{k=1}^{K} \omega_k P(\boldsymbol{U}|\theta_k), \tag{4}$$

where $P(\cdot)$ is the Gaussian distribution. Since the parameters $\{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \omega_k\}$ are unobserved, we introduce a new K-dimensional hidden variable $\boldsymbol{z}_n$ for user $\boldsymbol{u}_n$, in which a particular element z_{nk} is equal to 1, and the other elements are equal to 0.

In total, the goal of the EM algorithm is to find the maximum likelihood solution for models having unobserved variables [20]. The log-likelihood function of the observed variables $\boldsymbol{U}$ is expressed as

$$\log p(\boldsymbol{U}|\boldsymbol{\theta}) = \sum_{z} \log p(\boldsymbol{U}, \boldsymbol{Z}|\boldsymbol{\theta}), \tag{5}$$

where $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2, ..., \boldsymbol{\theta}_K\}$ is the set of all model parameters, while $\boldsymbol{Z}$ is the set of all latent variables with a corresponding row $\boldsymbol{z}_n^T$. The maximization of this function is divided into two steps. In the E step, the posterior $p(\boldsymbol{Z}|\boldsymbol{U}, \boldsymbol{\theta'})$ is used to find the expectation of the complete-user log-likelihood, which is defined as

$$Q(\boldsymbol{\theta}, \boldsymbol{\theta'}) = \sum_{z} p(\boldsymbol{Z}|\boldsymbol{U}, \boldsymbol{\theta'}) \log p(\boldsymbol{U}, \boldsymbol{Z}|\boldsymbol{\theta}), \tag{6}$$

where $\boldsymbol{\theta'}$ is the current parameter of the model, and $\boldsymbol{\theta}$ is the parameter that needs to be updated. The posterior distribution of the latent variables is evaluated by using the current parameter $\boldsymbol{\theta'}$. Thus, in the M step, the maximized quantity is the expectation of the complete-data log-likelihood, which can be expressed as follows,

$$\boldsymbol{\theta}^* = \arg\max Q(\boldsymbol{\theta}, \boldsymbol{\theta'}). \tag{7}$$

In conclusion, we propose an EM-based user clustering method for the fixed user scenario, shown in Algorithm 1.

Algorithm 1 The EM-based user clustering algorithm for fixed user scenario.

Input:
The user set, $\boldsymbol{U}$;
The number of clusters, K.
Output:
The parameters of each cluster, $\{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \omega_k\}$.
1: Choose an initial setting for the parameters $\boldsymbol{\theta'}$;
2: **E step**. Evaluate the posterior distribution using the current parameters, $p(\boldsymbol{Z}|\boldsymbol{U}, \boldsymbol{\theta'})$
3: **M step**. Re-estimate the parameters, given by
$$\boldsymbol{\theta}^* = \arg\max Q(\boldsymbol{\theta}, \boldsymbol{\theta'})$$
4: Evaluate the log-likelihood $\log p(\boldsymbol{U}|\boldsymbol{\theta})$, and check for convergence of either of the parameters or the log-likelihood. If not satisfied, then set $\boldsymbol{\theta'} \leftarrow \boldsymbol{\theta^*}$ and return to step 2.

3.2. Online EM-based method for dynamic user scenario

In dynamic user scenario, we assume that a new user $\boldsymbol{u}_{N+1}$ arrives at time $t+1$ and moves into one of the existed clusters $K^*(1 \leq K^* \leq K)$. The parameters of the user distribution at time t are denoted as $\boldsymbol{\theta}^t$. Based on the framework that was discussed in [21], we propose an online EM (OLEM) based method for fast user clustering. This method utilizes the information of the arriving user at time $t+1$ to update the sufficient statistics, i.e., the posterior distribution, in the E step by using the parameters at time t, which is denoted as

$$\begin{aligned}
&p^{t+1}(\boldsymbol{Z}|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t) = \sum_{j=1}^{K} p_j^{t+1}(\boldsymbol{z}_j|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t) \\
&= \sum_{j=1, j\neq K^*}^{K} p_j^{t+1}(\boldsymbol{z}_j|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t) + p_{j=K^*}^{t+1}(\boldsymbol{z}_j|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t) \\
&= \sum_{j=1, j\neq K^*}^{K} p_j^{t}(\boldsymbol{z}_j|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t) + p_{j=K^*}^{t+1}(\boldsymbol{z}_j|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t) \\
&= p^t(\boldsymbol{Z}|\boldsymbol{U}_N, \boldsymbol{\theta}^t) \underbrace{- p_{j=K^*}^{t}(\boldsymbol{z}_j|\boldsymbol{U}_N, \boldsymbol{\theta}^t) + p_{j=K^*}^{t+1}(\boldsymbol{z}_j|\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t)}_{\Phi_{j=K^*}(\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t)}.
\end{aligned} \tag{8}$$

So in the E step, we use (8) to update the sufficient statistics by adding the differences $\Phi_{j=K^*}(\boldsymbol{U}_{N+1}, \boldsymbol{\theta}^t)$ that are caused by the new arrival user in cluster K^*, without changing the sufficient statistics of the other clusters. In this way, the OLEM-based method reduces the computational complexity, which is lower than the complete EM-based clustering method. In the M step, the parameters are estimated in the same way as introduced in Algorithm 1. Therefore, the online EM-based user clustering method is summarized in Algorithm 2.

Algorithm 2 The OLEM-based user clustering for dynamic user scenario.

Input:
The user set $\boldsymbol{U}$;
The index of the changed cluster K^*.
The current parameters of the model, $\boldsymbol{\theta}^t$.
Output:
The new parameters of each cluster $\{\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k, \omega_k\}$.
1: Initialize the model by using the current parameters $\boldsymbol{\theta}^t$;
2: **E step**. Update the sufficient statistics by (8), $p^{t+1}(\boldsymbol{Z}|\boldsymbol{U}, \boldsymbol{\theta}^t)$
3: **M step**. Re-estimate the parameters, given by
$$\boldsymbol{\theta}^{t+1} = \arg\max Q(\boldsymbol{\theta}, \boldsymbol{\theta}^t)$$
4: Evaluate the log-likelihood $\log p^{t+1}(\boldsymbol{U}|\boldsymbol{\theta})$, and check for the convergence of either the parameters or the log-likelihood. If not satisfied, then set $\boldsymbol{\theta}^t \leftarrow \boldsymbol{\theta}^{t+1}$ and return to step 2.

4. SIMULATION RESULTS

In this section, the performances of our proposed unsupervised learning based user clustering methods are evaluated with computer simulations. We first construct the fixed user scenario. The downlink NOMA-based system consists of a BS and some users which have been physically clustered into $K = 2$ clusters. The number of users in clusters is set to $[5, 5]$. The system is assumed to work at $f_c = 28\ GHz$ frequency with bandwidth $W = 2\ GHz$. The users are generated by the generation model which is introduced in 2.1. The cluster centers are randomly distributed around the BS, in the region with radius $R_p = 5\ m$. The users are generated by the user distribution model with the radius $R_c = 1\ m$. After that, we construct the dynamic user scenario by creating some new users and moving them into some of the clusters. All the experiments in this paper are implemented on MATLAB.

4.1. Evaluation of the EM-based method

First, we evaluate the proposed user clustering method in fixed user scenario. To demonstrate the performance of our method, we conduct a comparison with some state-of-the-art user clustering methods, including the cluster-head-based clustering method in [12], and the status sort-based clustering method in [11]. In addition, we also investigate the performance of the NOMA-based system and the OMA-based system. The simulation result is shown in Fig.2.

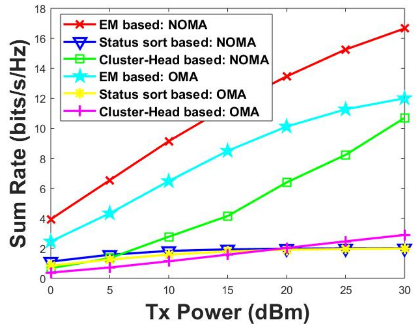


Fig. 2. Comparison of the sum-rates with different clustering algorithms in fixed user scenario.

In Fig.2, we can see that the sum-rate of our proposed method is larger than the other two methods, for either the NOMA-based or the OMA-based system. The increased transmission power leads to an increasing sum-rate of the system. In addition, it can be observed that the sum-rate of the NOMA-based system is larger than that of the OMA-based system. Therefore, the proposed EM-based user clustering method is competent for the NOMA-based system, and highly improves the spectrum efficiency and the total sum-rate.

4.2. Evaluation of the online EM-based method

In this part, we evaluate the proposed online user clustering method in dynamic user scenario. For comparison, we use the complete EM-based method which applied in fixed user scenario as a benchmark. Additionally, we compare the performance of our method for both NOMA-based and OMA-based systems. The experiment result is shown in Fig.3.

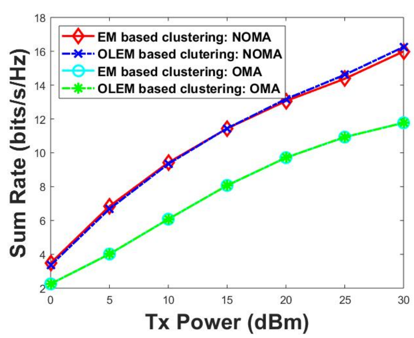
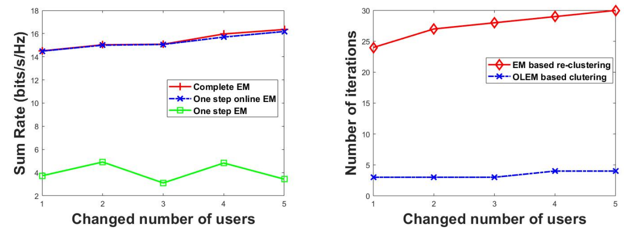


Fig. 3. Comparisons of the sum-rates between different clustering algorithms in dynamic user scenario.

From this figure, we can see that the OLEM-based user clustering method has almost the same performance as the complete EM-based re-clustering method, both for NOMA-based and OMA-based systems.

In addition, the computational complexity of these two methods is analyzed. We evaluate the clustering methods by two indicators, one is the system performance of using the fixed iterations, and another is the iteration number when convergence. The results are shown in Fig.4.



(a) Performance of one step iteration (b) Convergence speed

Fig. 4. The computational complexity of the two clustering methods.

In Fig.4(a), we can see that the one-step OLEM-based clustering method has nearly the same performance as the complete EM-based clustering, while the performance of one-step EM-based re-clustering is lower than the true system performance. In Fig.4(b), the convergence speed of OLEM-based clustering method is faster than the complete EM-based re-clustering method. Moreover, the system performance increases with the increased number of new users, while the number has little impact on the convergence speed of OLEM-based clustering method. However, the number of iterations is affected by the number of users when using the complete EM-based re-clustering method.

In general, the above results show that the performance of the OLEM-based method is the same as the complete EM-based method. However, the complete EM-based method needs to re-calculate the statistics of all users and re-estimate all the parameters, while the OLEM-based method only needs to update the statistics for a few users and fine-tune the parameters based on the previous user distribution model. Therefore, the OLEM-based method can considerably reduce the computational complexity and improve the effectiveness of the NOMA-based system.

5. CONCLUSION

In this paper, we focus on the NOMA-based system and investigate the optimization problem of sum-rate maximization. First, we have constructed the system model in two scenarios, i.e., fixed user scenario and dynamic user scenario. After that, we have proposed an EM-based algorithm for the fixed user scenario. Since the users keep arriving in the real-time system, we have constructed a dynamic user scenario and developed an OLEM-based clustering algorithm. Simulation results have demonstrated the effectiveness of our proposed EM-based method for the fixed user scenario and the online EM-based method for the dynamic user scenario. Moreover, the results have shown that the proposed OLEM-based user clustering method can reach the same or better performance compared to the complete EM-based method in dynamic scenario.

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