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Modularity-based Dynamic Clustering for Energy Efficient UAVs aided Communications

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***Abstract*—In this letter, we propose a novel modularity-based dynamic clustering relying on modified Louvain method for UAVs aided mobile communications. Our aim is to save the transmit power of the mobile devices, by locating the UAVs vertically projected on the centroids of the user clusters. We further propose two types of operation for the modularity-based dynamic clustering, namely the recurring operation and the differential operation. We show that the proposed method requires substantially lower transmit power of the mobile devises and lower energy consumption of the UAVs than that required by the K-means based solution. We also show that the differential operation is more suitable for networks with lower proportion of moving users, since it consumes significantly less energy than that required by the recurring operation at the cost of requiring slightly higher transmit power of mobile devices.**

I. INTRODUCTION

Recently, unmanned aerial vehicles (UAVs) aided mobile communications has drawn great attentions, thanks to its capability in providing better line-of-sight (LoS) connections with adjustable flying positions. The use cases of the UAVs aided mobile communications mainly cover emergency-responding services for both public and military areas [1]. Recent studies have investigated various air-to-ground channel models [2], flying altitude versus coverage trade-offs [3], energy efficient UAV transmission schemes [4], etc. Indeed, it is highly important to save the transmit power of mobile devices so that to prolong their usage in emergency scenarios. One promising approach is to locate the UAVs closer to the mobile devices for establishing shorter radio links. To elaborate, [5] showed that the transmit power of mobile devices can be substantially reduced by adapting the UAVs' positions based on the mobile devices' locations.

In UAVs aided mobile communications, each UAV serves a cluster of mobile devices, where the clustering is typically based on the *de facto* K-means criteria. However, it is known from network science that *modularity* is the most used and best measure of the quality of clustering performance. Indeed, it has been widely studied in sociology, biology and computer science in terms of community detection [6]. Hence, *we propose a novel modularity-based dynamic clustering for energy efficient UAVs aided mobile communications, relying on modified Louvain method in both recurring and differential operation to construct clusters.* Specifically, after forming dynamic clusters, the UAVs are relocated to the positions vertically projected on the centroids of clusters.

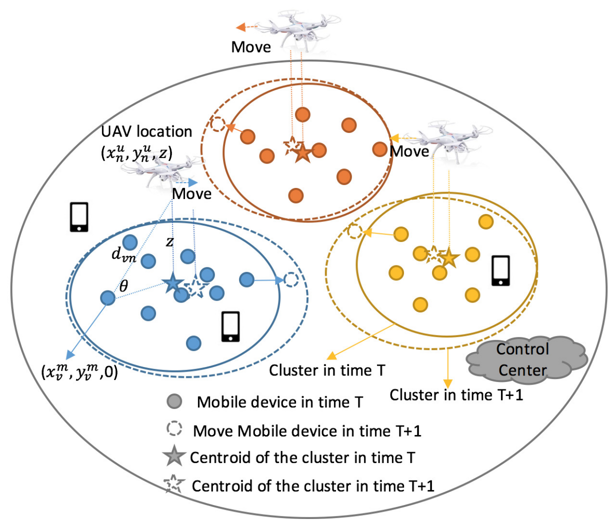

Fig. 1. Unmanned aerial vehicles aided mobile communications system.

The rest of the paper is organized as follows. In Section II, the system model is presented. In Section III, the construction of modularity-based dynamic clusters is included. Simulations and conclusions are finally provided in Section IV and V.

II. SYSTEM MODEL

Fig. 1 illustrates a typical UAVs aided mobile communications system, consisting of multiple UAVs, clusters of mobile devices and a control centre. Let $\mathcal{V} = \{1, 2, ..., V\}$ be the set hosting V mobile devices and $\mathcal{N} = \{1, 2, ..., N\}$ be the set hosting N UAVs serving these mobile devices. Similar to [4], we use orthogonal resources for communications between multiple UAVs and mobile devices, and hence there is no interference presented in this system. In this paper, we allow each UAV serve a cluster of mobile devices, and hence there are a total of N non-overlapping clusters. Furthermore, we define the coordinates of the vth mobile device and the nth UAV as $\{x_v^m, y_v^m, 0\}$ and $\{x_n^u, y_n^u, z\}$, respectively. Also, the xy-coordinates of the nth UAV are set as the centroid of the nth cluster $\mathcal{C}_n$. We finally assume that all coordinates are perfectly known to the control centre[1].

[1]Control center is responsible to detect and track the UE's movement, which could be achieved through conventional/new positioning techniques.

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In UAVs aided mobile communications, it is reasonable to aim at a specific data rate R_b with a fixed modulation scheme, such as the quadrature phase shift keying (QPSK) modulation employed in this paper. In order to reach a target bit error rate of δ at the nth UAV, the transmit power P_{vn}^m required for the vth mobile device in the uplink is [2]

$$P_{vn}^m(\mathcal{C}_n) = \left[Q^{-1}(\delta)\right]^2 \frac{R_b N_0}{2} 10^{\eta/10} \left[\frac{4\pi f_c d_{vn}(\mathcal{C}_n)}{c}\right]^\alpha, \quad (1)$$

where $Q^{-1}(\cdot)$ is the inverse of Q-function, N_0 is the noise power spectral density, η is the excessive path-loss, f_c is the carrier frequency, c is the speed of light and $\alpha = 2$ is the free space path-loss exponent. Finally, d_{vn} is the distance between the vth mobile device and the nth UAV, which is

$$d_{vn}(\mathcal{C}_n) = \sqrt{(x_v^m - x_n^u)^2 + (y_v^m - y_n^u)^2 + z^2}. \quad (2)$$

Explicitly, our aim is to minimise the total transmit power of all mobile devices, which can be formulated as

$$\min_{\mathcal{C}_n} \sum_{n\in\mathcal{N}} \sum_{v\in\mathcal{C}_n} P_{vn}^m(\mathcal{C}_n), \quad (3)$$

$$\text{s.t.} \quad \mathcal{C}_n \cap \mathcal{C}_w = \varnothing, \qquad n \neq w, n, w \in \mathcal{N}, \quad (4)$$

$$\sum_{n\in\mathcal{N}} |\mathcal{C}_n| = V. \quad (5)$$

The problem of (3) is a combinatorial problem, where the full enumeration of $\mathcal{C}_n$ is computationally unaffordable. As a result, heuristics in constructing clusters are required, where it is also important to construct dynamic clusters and adapt UAVs' positions accordingly.

III. Modularity-based Dynamic Clustering

A. Preliminaries

We advocate a network graph based clustering approach. To this end, we first construct a so-called *adjacency* matrix A of size $V \times V$ with all entries being initialised to zero. Then, we set the (i,j)th entry of A to unity, if the distance between the ith and jth mobile device is less than a proximity threshold of d_τ. Hence, it is easy to see that the adjacency matrix A is an undirected symmetric matrix.

To carry out unsupervised clustering, we adopt *modularity* as the quality measure for clustering performance by evaluating and comparing the 'closeness' inside and between clusters of a given network graph described by its adjacency matrix A. Explicitly, the modularity value Q is [6]

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m}\chi(i,j)\right], \quad (6)$$

where m is the total weight of all edges in the network graph, A_{ij} is the weight of the edge between the ith and jth mobile device, $k_i = \sum_j A_{ij}$ is the total weight of the edges attached to the ith mobile device and finally $\chi(i,j)$ indicates if the ith and jth mobile devices belong to the same cluster.

B. Modified Louvain Method

The Louvain method is a powerful unsupervised clustering heuristic aimed to achieve the maximal value of Q. It is carried out by iteratively evaluating the modularity *gain* when merging mobile device i with cluster $\mathcal{C}_n$, where the gain is [7]

$$\Delta Q = \frac{k_{i,in}}{m} - \frac{\sum_t k_i}{2m^2}, \quad (7)$$

where $\sum_t$ is the total weight of the edges incident to all mobile devices in cluster $\mathcal{C}_n$ and $k_{i,in}$ is the total weight of the edges from mobile device i to all mobile devices in cluster $\mathcal{C}_n$. Formally, each mobile device is initialized as an individual cluster, and the iterative procedure is then carried out as follows,

1) for each mobile device, we evaluate ΔQ when removing this mobile device from its present cluster and adding it to the other clusters in sequence. In this way, each mobile device will be merged with the cluster having the maximal value of ΔQ (in case of the same ΔQ, random merge decision would be made). Otherwise, this mobile device will stay isolated, if there are no modularity gains.
2) the clusters found in the previous stage will form new 'virtual' mobile devices in the network graph. To this end, the weight of the edge between two 'virtual' mobile devices is given by the total weight of the edges between mobile devices within the respective two clusters. Then the first stage is applied again.

The above stages are iterated until there is no further modularity gain. We then make *modifications* to arrive at a desired number of clusters as shown in Algorithm 1. With regards to the complexity, for modified Louvain method, the complexity appears as $O(vlog(v))$, where v is the total number of mobile devices. The complexity of K-means algorithm is $O(vnlr)$ [8], [9], in which l means the dimension of the nodes, n is the total number of clusters and r is the iterations of the computation.

C. Dynamic Clustering

When the structure of the network graph is slowly-varying, for example in case of moving devices, we propose two types of operation of the modified Louvain method. Explicitly, the *recurring* operation refers to apply the modified Louvain method every time the network is changed. By contrast, the *differential* operation refers to apply the modified Louvain method by only considering the incremental dynamics. Specifically, we treat the moving devices as first removing them from the network graph and then adding them again with new locations. Explicitly, the differential operation is as follows

1) when removing mobile devices, we keep the remaining clustering decisions unchanged, whilst generating a reduced network graph.
2) when adding mobile devices, we re-evaluate the modularity gain of (7) over the reduced network graph for each existing cluster, which the newly added mobile devices would like to merge with.

For example, Fig. 2 depicts the operation of moving mobile device #6 in the network graph. The sub-figure (a) on the top left is the modified Louvain clustering result in time T, where

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Algorithm 1 Louvain Method with Fixed Number of Clusters

Require: Louvain clustering with constraint as fixed number of clusters
Input: Symmetric adjacency matrix A, Required Cluster number R
Output: Vector of cluster IDs C
 Initialization Assignment of vector of cluster IDs C
 for $i = 1, 2, ...,$ total number of nodes **do**
  for $j = 1, ...,$totoal number of neighbours **do**
   if Total cluster number $> R$ **then**
    Calcualte ΔQ as in equation (7). If $\Delta Q > -1$, $C_{new}(i) \leftarrow C(j)$. {Set a constraint of the situation to stop calculating ΔQ}
   end if
  end for
  if $\Delta Q > 0$ **then**
   $C(i) \leftarrow C_{new}(i)$.
  else if $\Delta Q <= 0$ and current total cluster number $> R$ **then**
   $C(i) \leftarrow C_{new}(i)$. {Find the optimum decision if pre-set cluster number is less than the true Louvain clustering results}
  end if
 end for
 Merge clusters and generate reduced network $C_{reduced}$, update symmetric adjacency matrix A, repeat previous steps.

Algorithm 2 Update Adjacency Matrix for Dynamic Network

Require: Update symmetric adjacency matrix A when points are removed or added.
Input: Vector of previous cluster IDs $C_{previous}$, Number of moving points $MoveNumber$.
Output: Updated symmetric adjacency matrix A.
 if Remove total moving points from network **then**
  $C_{new} \leftarrow C_{previous}(1 : (end - MoveNumber))$
 else Add new location of total moving points in network
  $C_{new}(1 : end) \leftarrow C_{previous}$
  $C_{new}((end+1) : (end+MoveNumber)) \leftarrow$ Previous total cluster number$+(1 : MoveNumber)$
 end if
 Update symmetric adjacency matrix A based on C_{new}.

a total of 11 mobile devices are divided into three clusters, in blue, yellow and orange colours, respectively. On the bottom right sub-figure (d), mobile device #6 is added to the blue cluster in time $T + 1$ with new edge connections attached to mobile device #4 and #8. Instead of re-applying the modified Louvian method from scratch, in differential fashion, we first remove mobile device #6 from the network graph as shown in sub-figure (b) and then add 'new' mobile device #6 to the network graph as shown in sub-figure (c), by keeping the clustering result of the remaining mobile devices in time T unchanged. During this process, the adjacency matrix A can be updated as in Algorithm 2.

The principle of differential fashion is to consider only local modularity change, rather than aiming for global modularity

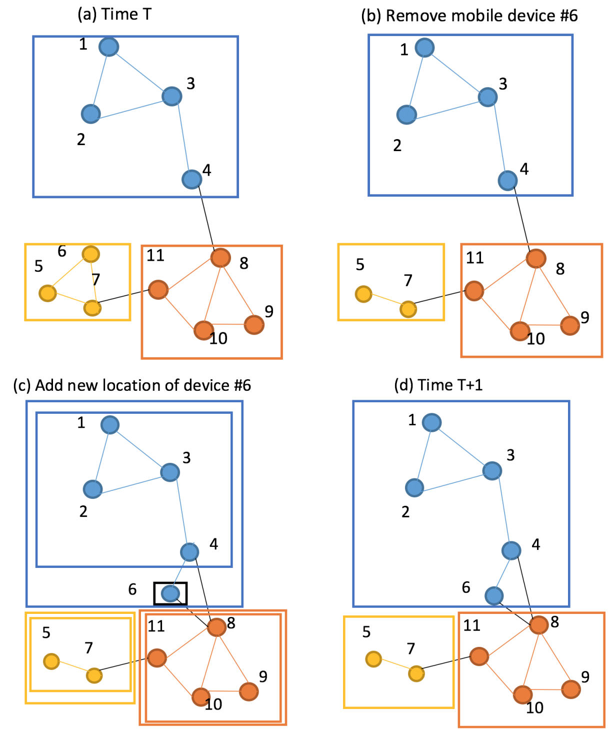

Fig. 2. Differential fashion of the modified Louvain method based clustering.

maximization as for recurring fashion. Hence, the differential fashion will be more computationally efficient than the recurring fashion, yet it is still robust to introduce only small changes of UAVs' positions. However, we do not expect the use of the differential fashion in fast-varying network graph structure inured by large scale movements.

D. UAV Relocation

Once the clusters are formed, the UAVs need to be relocated to the new positions vertically projected on the corresponding centroids of the new clusters. The aim is to let UAVs travel as short as possible for saving their energy. This is a classic assignment problem and we use below greedy approach to schedule which UAV is relocated to which cluster,

1) we first construct a distance matrix B, where its (n, j)th entry records the distance between the nth UAV's current location and the destination of the jth new cluster.
2) find the entry of B having the shortest distance to form a trajectory and delete the corresponding row and column to construct a reduced and updated distance matrix.
3) repeat the previous steps until all trajectories are formed.

Other relocation methods are out of scope, since we want to focus on the modularity-based dynamic clustering.

IV. Numerical Results

In our simulation, mobile devices are distributed within a 1km $\times$ 1km area obeying spatial Poisson Point Process (PPP). We define moving ratio as the number of moving devices with respect to the total number of mobile devices. These devices move every time slot with step size of 10m towards a randomly chosen direction uniformly drawn within 360^o. Furthermore,

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TABLE I
SIMULATION PARAMETERS

Parameter	Description	Value
δ	Bit error rate requirement	10^{-8}
N_o	Noise power spectral density	-170 dBm/Hz
R_b	Transmission data rate	200 Kbps
η	Additional path loss to free space	5 dB
f_c	Carrier frequency	2 GHz
s	UAV speed	10 m/s
z	UAV height	500 m
d_τ	Proximity threshold	200 m

the moving energy consumption of the UAV is given by [4] $E(D, s) = D(0.95s^2 - 20.4s + 130)$, where D is the total moving distance of UAV in one calculation time slot and s is the speed of UAV. The total number of UAVs is set to $N = 7$, and hence we have 7 clusters within the network. Finally, Table I shows the rest of the simulation parameters.

Fig. 3 shows the comparisons of the average total transmit power of mobile devices and the average moving energy consumption per UAV when using K-means and modified Louvain method based clustering in recurring operation, over 250 times independent runs lasting 100 time slots each and with the moving ratio set to $1/5$. It is very clear to see that the proposed modularity-based clustering method only requires roughly half of the average total transmit power of mobile devices when compared to the classic K-means based clustering, for all the density settings of mobile devices. With respect to the average moving energy consumption per UAV, the proposed modularity-based clustering method also exhibits beneficial savings when compared to the K-means based clustering, although their difference tends to be smaller when the density of mobile devices becomes higher.

Fig. 4 shows the comparisons of the total transmit power of mobile devices and the total moving energy consumption of UAVs on per time slot basis when expressed as the ratio between using recurring and differential operation of the modified Louvain method, over 250 times independent runs and with various moving ratios. It can be seen from the top subfigure that the differential operation results into an increased total transmit power of mobile devices across all time slots considered. This increase remains constantly small when the moving ratio is low, but it grows quickly when the moving ratio is high. By contrast, from the bottom sub-figure, it is plausible that the differential operation substantially reduces the moving energy consumption of UAVs for all time slots considered, where the energy saving is particularly high when the moving ratio is low.

V. CONCLUSIONS

We proposed a novel modularity-based dynamic clustering relying on the modified Louvain method for energy efficient UAVs aided mobile communications. Our solution is promising in reducing both the transmit power of the mobile devices and the energy consumption of the UAVs when compared to those required by the conventional benchmark. The further designed differential operation of our method is found more favourable in networks with low moving ratio, while the recurring operation is inevitable for high moving ratio. In our future work, we will incorporate specific mobility model of UEs, flying model of UAVs and various spectrum planning solutions.

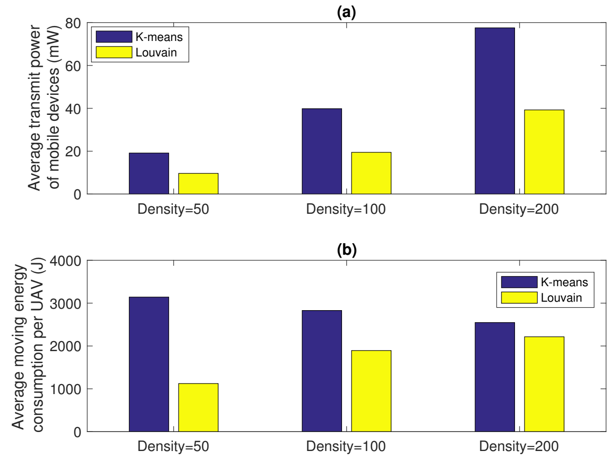

Fig. 3. Comparisons of the average total transmit power of mobile devices and the average moving energy consumption per UAV when using K-means and modified Louvain method based clustering in recurring operation, over 250 times independent runs lasting 100 time slots each and with the moving ratio set to $1/5$.

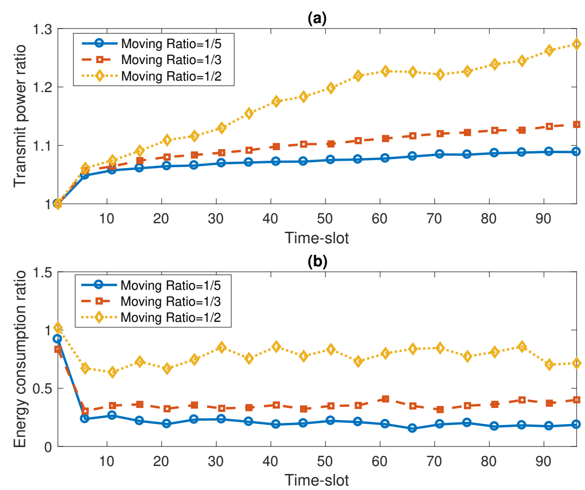

Fig. 4. Comparisons of the total transmit power of mobile devices and the total moving energy consumption of UAVs on a per time slot basis when expressed as the ratio between using recurring and differential operation of the modified Louvain method, over 250 times independent runs and with various moving ratios.

REFERENCES

[1] D. Orfanus, E. P. de Freitas, and F. Eliassen, "Self-organization as a supporting paradigm for military UAV relay networks," *IEEE Communications Letters*, vol. 20, no. 4, pp. 804–807, April 2016.

[2] A. Al-Hourani, S. Kandeepan, and A. Jamalipour, "Modeling air-to-ground path loss for low altitude platforms in urban environments," in *IEEE Global Communications Conference*, Dec 2014, pp. 2898–2904.

[3] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Mobile unmanned aerial vehicles (UAVs) for energy-efficient internet of things communications," *IEEE Transactions on Wireless Communications*, vol. 16, no. 11, pp. 7574–7589, Nov 2017.

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[4] ——, "Mobile internet of things: Can UAVs provide an energy-efficient mobile architecture?" in *IEEE Global Communications Conference*, Dec 2016, pp. 1–6.

[5] ——, "Optimal transport theory for power-efficient deployment of unmanned aerial vehicles," in *IEEE International Conference on Communications*, May 2016, pp. 1–6.

[6] M. E. Newman, "Modularity and community structure in networks," *Proceedings of the national academy of sciences*, vol. 103, no. 23, pp. 8577–8582, Jun 2006.

[7] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, "Fast unfolding of communities in large networks," *Journal of statistical mechanics: theory and experiment*, vol. 2008, no. 10, p. P10008, Oct 2008.

[8] J. A. Hartigan and M. A. Wong, "Algorithm as 136: A k-means clustering algorithm," *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, vol. 28, no. 1, pp. 100–108, 1979.

[9] M. Sanderson, D. Christopher, H. Manning *et al.*, "Introduction to information retrieval," *Natural Language Engineering*, vol. 16, no. 1, p. 100, 2010.