Multistage Clustering-Based Localization for Remote UAV Swarm: A Coalitional Game Framework

Lang Ruan, Guangxia Li, Jian Cheng, Jing Lv, Weiheng Dai, Shiwei Tian, and Jing Hu

***Abstract*— In the GNSS-denied localization scenario, only received signals and corresponding distance measurements are available. Based on that, in this letter, we construct a multistage clustering-based model for UAV swarm. We characterize the proposed model as a coalition formation game (CFG) and provide corresponding preference criteria for algorithm design. A tree-like multistage clustering mechanism is adopted based on a coalitional graph game (CGG). Each cluster (local map) performs localization calculation and then merges through neighboring drones (NDs) stage by stage. The simulation results show that the proposed scheme can achieve better localization accuracy than the comparison algorithms and is more robust for irregular network topologies.**

***Index Terms*— UAV localization, multistage tree-like clustering, multiple dimensional scaling, coalitional games.**

I. Introduction

UNMANNED aerial vehicles (UAVs, also referenced as drones) has the superiority of large-scale, rapid, and flexible deployment. In the GNSS-denied environment, UAV swarms can effectively support communication devices to perform localization. Likewise, the positions of UAV swarms are also crucial for their mission execution.

This letter implements ultra-wideband (UWB) technology, whereby received signals and corresponding distance measurements are available for localization. For swarming localization, multiple dimensional scaling (MDS) [1] is frequently used, especially when obtaining a complete Euclidean distance matrix (EDM). MDS-MAP adds absolute coordinate mapping. The core of MDS is Singular Value Decomposition (SVD). Due to complex electromagnetic environments, such as remote distance, multipath propagation, and NLOS, distance measurements encounter a significant deviation or even failure, which reduces the accuracy of localization technology. MDS-MAP (P) [1] sufficiently alleviates the calculation error by hop-based clustering. Many MDS-based works employ matrix completion methods such as the shortest path information [1] and SVD-MDS [2], [3]. Chen *et al.* in [4] proposed an improved SMDS and improves the localization accuracy by relaxing the fully connected requirements, which requires angle information. In [5], we improved MDS-MAP (P) by presenting a CFG-based two-stage clustering scheme.

However, all those clustering schemes cannot adapt well to different topologies of networks and sometimes fall into the dilemma of error accumulation. Based on this, we propose a novel clustering-based robust scheme in remote swarming localization, and the work is described as follows:

- This letter constructs a multistage clustering-based model. We introduce anging packet losses (RPLs) using received signals and further characterize the O-EDM rate, which is tightly coupled with localization performance.
- We present a tree-like multistage scheme for clustering-based localization. Then, a coalitional game framework is adopted to explore the characteristics of the model. Then, we design localization algorithms based on the proposed game model. Simulation results show that the proposed methods effectively reduce RPLs and achieve better localization performance in different network topologies and remote scenario compared with comparison algorithms.

The main differences of our work with others can be summarized as: 1) Different from hop-based clustering [1]–[4], this letter performs clustering for swarm based on the O-EDM rate. 2) Compared with the previous CFG-based clustering scheme in [5], a tree-like multistage clustering scheme based on CGG is designed to learn the optimal clustering and is more robust for irregular network topologies. This letter adopt asymmetric double-sided two-way ranging (ADS-TWR) in the time-of-flight (TOF) localization. Moreover, the physical layer and MAC layer of the system are designed regarding the IEEE 802.15.4-2011 UWB standard [6].

The rest of the letter is organized as follows. Section II shows the system model & problem formulation for multistage clustering-based localization. Section III analyzed a CFG approach for system model, and built a CFG-based cooperative localization scheme. Simulation results are presented in Section IV. Finally, Section V gives the concluding remarks.

II. Multistage Clustering-Based Localization System Model for Remote UAV Swarm

We consider a remote localization scenario for UAV swarm with GNSS denied, which consists of N drones, denoted by $\mathcal{N} = \{1, 2, \dots N\}$, and N_1 ground stations (GSs), denoted by $\mathcal{N}_1 = \{N+1, N+2, \dots, N+N_1\}$. System duration is evenly divided into T discrete slots, denoted by $\mathcal{T} = \{1, 2, \dots T\}$. GSs are placed to: 1) Communicate with drones and give commands; 2) Act as anchors to determine the coordinate system. Communication links among GSs are available. The objective of our scenario is to achieve optimal localization performance for UAV swarm based on relative ranging information. For ease of representation, we identify UAV and GS

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collectively as communication user (CU). Denote the position of CU $n \in \mathcal{N}_2 = \{\mathcal{N}_1 \cup \mathcal{N}\}$ as $\mathbf{p}_{n,t} = [x_{n,t}, y_{n,t}, z_{n,t}]$. The elevation $z_{n,t}$ can be obtained by the barometer equipped with drones. Define $\mathbf{D}^{\mathrm{r}} = [d_{n,k}] \in \mathbb{R}^{N_2 \times N_2}$ as the EDM of the whole network, where $d_{n,k}(t) = \|\mathbf{p}_{n,t} - \mathbf{p}_{k,t}\|$ is the Euclidean geometric distance between CU n & k, $k \in \mathcal{N}_2$ ($\|\cdot\|_2$ is the L2-norm), $N_2 = N + N_1$. CUs receive relative ranging information using ranging devices. ADS-TWR minimizes the measurement error in TOF calculation, which does not require the same response time on every device [7]. Define $\mathbf{H}^{\circ} = [r_{n,k}] \in \mathbb{R}^{N_2 \times N_2}$ as the observed EDM (O-EDM). Due to remote localization, there occurs losses of ranging values in $\mathbf{H}^{\circ}$ which we call RPLs.

Denote available channels as $\mathcal{C} = \{1, 2, \ldots, C\}$, where B_c is the bandwidth of $c \in \mathcal{C}$. To accurately describe the ranging and transmission under UAV-assisted communications, this letter introduces the UAV-to-X (U2X) channel model [8], [9]. Suppose there are no interferences since CUs transmit messages in sequence in ADS-TWR. Thus, the received power of the signal from CU n to k over channel c is:

$$\mathrm{Pr}_{n\to k}^{c}(t) = \begin{cases} \mathrm{Pt}_n \cdot G \cdot d_{n,k}^{-\alpha}(t) \cdot \varepsilon_t^1, & \text{U2U Com [9]}, \\ \mathrm{Pt}_n / 10^{\mathrm{PL}_{n,k}^{c}/10} \cdot \varepsilon_t^2, & \text{U2N Com [10]}, \end{cases} \tag{1}$$

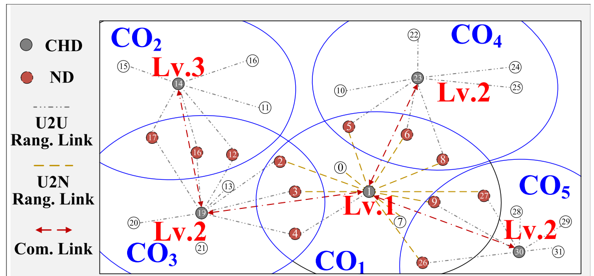
where Pt_n^c is the transmit power of U n, ε_t^1 & ε_t^2 are the instantaneous fading coefficient. G is the constant power gains factor introduced by amplifier and antenna. For UAV-to-UAV (U2U) channel model, the path loss is given by the Friis equation. Suppose the path-loss factor is α. $d_{n,k}^{-\alpha}(t) \cdot \varepsilon_t^1$ represents the pathloss in U2U links. For UAV-to-network (U2N) channel model, the path loss from n to k over channel c is expressed as $\mathrm{PL}_{n,k}^{c}(t) = \mathrm{P}_{\mathrm{LoS},n}(t) \cdot \mathrm{PL}_{\mathrm{LoS},n}^{c}(t) + \mathrm{P}_{\mathrm{NLoS},n}(t) \cdot \mathrm{PL}_{\mathrm{NLoS},n}^{c}(t)$, where the LoS & NLoS pathloss $\mathrm{PL}_{\mathrm{LoS},n}^{c}$ & $\mathrm{PL}_{\mathrm{NLoS},n}^{c}$ are given from [9], [10]. $\mathrm{P}_{\mathrm{LoS},n}(t) = \left(1 + a \exp\left(-b\left(\theta_{n,k}(t) - a\right)\right)\right)^{-1}$ is the probability of LoS connection, $\theta_{n,k}$ is the elevation angle from n to k, $\mathrm{P}_{\mathrm{NLoS},n}(t) = 1 - \mathrm{P}_{\mathrm{LoS},n}(t)$. Hence, the received signal-to-noise ratio (SNR) from n to k is:

$$\eta_{n\to k}^{loc}\left(\mathbf{p}_{n,t}, \mathbf{p}_{k,t}, \mathrm{Pt}_n\right) = \sum_{c=1}^{C} \left(a_{n,c}(t) \cdot a_{k,c}(t) \cdot \frac{\mathrm{Pr}_{n\to k}^{c}(t)}{N_0 B_c} \right), \tag{2}$$

where N_0 is the noise power per unit bandwidth. $a_{n,c}(t) = 1$ shows that CU n accesses channel c, while $a_{n,c}(t) = 0$ dose not. Eq. (2) shows that successful communication between CU n & k only occurs when they access the same channel c. Considering that ADS-TWR requires demodulating signals of both bidirectional U2X links for calculation, we define $\eta_{n,k}^{loc}\left(\mathbf{p}_{n,t}, \mathbf{p}_{k,t}, p_n\right) = \min\left(\eta_{n\to k}^{loc}(\cdot), \eta_{k\to n}^{loc}(\cdot)\right)$ (abbreviated as $\eta_{n,k}^{loc}(t)$, $\eta_{n,k}^{loc}(t) = \eta_{k,n}^{loc}(t)$). To characterize RPL, we define the indicator function $\phi_{n,k}(t)$ as follows:

$$\phi_{n,k}(t) = \begin{cases} 0, & \eta_{n,k}^{loc}(t) \geq \eta_{\min}, \\ 1, & \eta_{n,k}^{loc}(t) < \eta_{\min}, \end{cases} \tag{3}$$

where $\eta_{\min}$ is the minimal demodulation threshold of the signal. $\phi_{n,k}(t)$ indicates that whether the ranging is successfully performed. Denote $\mu_{n,k}$ as the measurement error, then the observed ranging value is expressed as $r_{n,k} = \phi_{n,k}(t) \cdot (d_{n,k} + \mu_{n,k})$. The RPLs of the received signal in the whole network is then $\Phi_{\mathcal{N}_2}(t) = \sum_{n=1}^{N_2-1} \sum_{k=n+1}^{N_2} \phi_{n,k}(t)$. To alleviate RPLs $\Phi_{\mathcal{N}_2}(t)$, this letter proposes:



Cluster	CO_1	CO_2	CO_3	CO_4	CO_5
Stage st_m	1	3	2	2	2
Superior Cluster st_m^+	ϕ	3	1	1	1
Subordinate Cluster st_m^-	[3, 4, 5]	ϕ	2	ϕ	ϕ

Fig. 1. Tree-Like multistage clustering schematic diagram for remote swarming localization (part of the rang. & com. links are presented).

Multistage Clustering Scheme for Swarming Localization. In this scheme, the swarm are clustered based on the received SNR matrix $\boldsymbol{\Theta} = [\eta_{n\to k}] \in \mathbb{R}^{N_2 \times N_2}$. The network consists of M clusters, denoted by $\mathcal{M} = \{1, 2, \ldots, M\}$, $1 \leq M \leq N_2$. Denote c_n as the cluster selection of CU n, then $CO_m = \{n \in \mathcal{N} | c_n = m\}$ represents the set of CUs belonging to cluster m. Besides, suppose $CO_{m_1,m_2} = CO_{m_1} \cup CO_{m_2}$. The other elements are as follows: (1) **Cluster head drones (CHDs)**: CHDs are deployed as relays among clusters to optimize communication performance, denoted by ch_m; (2) **Neighboring drones (NDs)**: NDs are overlapping drones between two adjacent clusters, deployed as anchors to realize local map fusion. Denote cluster m's ND set as $\mathcal{B}_m \in CO_m$. ND $n \in \mathcal{B}_m$ belongs to two clusters, i.e., $card\,(c_n) = 2$ & $c_n = [m_1, m_2]$. Denote $\mathcal{E} = [\varepsilon_{m_1,m_2}] \in \mathbb{R}^{M \times M}$ as the set of links within clusters, then $\varepsilon_{m_1,m_2} = 1$; (3) **Cluster stage**: Each cluster m is assigned a stage, denoted by st_m, which depends on the direction of the map merging. For cluster m, we denote its superior & subordinate cluster as st_m^+ & st_m^-, representing the clusters connected to cluster m, i.e. $\varepsilon_{m,st_m^+} = \varepsilon_{m,st_m^-} = 1$. $st_m^+ = \phi$ or $st_m^- = \phi$ indicates no superior or subordinate stage cluster for cluster m.

As shown in Figure. 1, the network forms five clusters ($M = 5$), the table below shows the stage, superior & subordinate of each cluster. For CO_2 ($st_2 = 2$), its superior & subordinate cluster are CO_1 ($st_2^+ = 1$) and CO_3 ($st_2^- = 3$) respectively. Each cluster compute its local map through intra-cluster localization; and then merge local maps from stage 1 (Lv. 1) to stage 3 (Lv. 3) to form a global map utilizing NDs. Hence, RPLs between coalition m_1 & m_2 are:

$$\Phi_{m_1,m_2}(t) = \sum_{n \in CO_{m_1}} \sum_{\substack{k \in CO_{m_2} \\ n \neq k}} \phi_{n,k}(t). \tag{4}$$

$\Phi_{m,m}(t)$ is abbreviated as $\Phi_m(t)$. $\Phi_{\mathcal{N}_2}(t)$ is then reconstructed as $\sum_{m=1}^{M} \Phi_m(t)$. There exists a negative correlation between RPL and localization performance. Define the O-EDM without missing RPLs as a complete O-EDM, we then present the O-EDM rate of the cluster m, which is:

$$\psi_m(t)(\%) = \frac{\Phi_m(t)}{\Phi_m^{\mathrm{cmp}}} = \frac{\Phi_m(t)}{\mathrm{card}\,(CO_m)^2 - \mathrm{card}\,(CO_m)}, \tag{5}$$

where Φ_m^{cmp} is the number of ranging values for cluster m with a complete O-EDM. $\psi_m(t)$ (Max. 100%) reflects the relationship between RPLs and localization performance intuitively and has a theoretically optimal value. Our work aims to find an optimal solution for clustering ($\{c_n\}_{n\in\mathcal{N}_2}$) and multistage mechanism ($\{st_m, st_m^+, st_m^-\}_{m\in\mathcal{M}}$) to achieve maximal O-EDM rate of the whole network, which is:

$$\mathcal{P}_1 : \left[\left\{st_m, st_m^+, st_m^-\right\}_{m\in\mathcal{M}}, \{c_n\}_{n\in\mathcal{N}_2}\right] = \arg\max \sum_{m=1}^{M} \psi_m(t). \tag{6}$$

The proposed model can achieve optimal localization performance utilizing $\psi_m(t)$. The following section models the problem as coalitional games and presents solutions.

III. Problem Solution & Algorithm Design

This section solves the clustering scheme and then introduces a tree-like multistage mechanism based on coalitional games (CG). Firstly, we present the clustering algorithm under the proposed CG framework (Algorithm. 1, CG-Tree Loc Algo) and then prove the convergence and stability. Then, we adopt the localization algorithm. "Coalition" refers to "Cluster" in the following description.

A. Clustering-Based UAV Swarm for Remote Localization Constructed as a Coalition Formation Game

The proposed localization model satisfies the characteristic of the cooperative game. In this subsection we construct the proposed UAV swarm clustering model as a coalition formation game (CFG), which is characterized as $\mathcal{G} = \left(\mathcal{N}, \{c_n\}_{n\in\mathcal{N}}, V\right)$. Set $\Pi = \{CO_m\}_{m=1}^{M}$ which partitions $\mathcal{N}$. $V(CO, \Pi)$ is the utility function, indicating the total payoff generated by any coalition CO, and is characterized as follows: $V(CO, \Pi) = \psi_m(t)$.

Coalition selection rule (CSR is proven that the merge & split effect can be achieved by a certain number of CS rules or switch rules [11], while avoiding the batch strategy selection of CUs. Log-linear learning is adopted for coalition updates to avoid local optimum caused by the diversity of strategy sets. Denote $V^* = V(CO, \Pi^*) + V(CO^*, \Pi^*)$, $V = V(CO, \Pi) + V(CO^*, \Pi)$. Set $\beta > 0$ as the learning parameter, then we describe the update condition as follows:

$$\text{Prob}\left(\Pi = \Pi^*)\right) = \frac{\exp\left\{\beta \cdot (V^* + V)\right\}}{\exp\left\{\beta \cdot V\right\} + \exp\left\{\beta \cdot V^*\right\}}. \tag{7}$$

Therefore, even if the CU's strategic choices have stalled, it may still be on track soon.

Remark 1: With the preference relation of coalition order and coalition selection/switch rule, $\mathcal{G}$ can be converged to the stable coalition partition under Algorithm. 1.

Theoretical analysis can refer to Section III (D) in [5]. Note that O-EDM rate has performance upper bound (100 %), the stable structure is generally the optimal solution of $\mathcal{G}$. After coalition formation, coalitions need to determine their stages, so as to ensure a lower cumulative localization errors.

B. Tree-Like Multistage Mechanism Design Based on Coalitional Graph Games

Learning from the concepts of coalitional graph games (CGG) [12], we innovatively take coalitions as players in the CGG and construct $\mathcal{G}_2(\mathcal{M}, \boldsymbol{\varepsilon})$, where $\boldsymbol{\varepsilon}$ is the set of all edges (CO-to-CO links). For any coalition $m_1, m_2 \in \mathcal{M}$, we say the link exists, if $\varepsilon_{m_1,m_2} = 1, \varepsilon \in \boldsymbol{\varepsilon}$. Next, we introduce feasible local strategy from [13]. This part is reflected in line 7-18 of Algorithm 1. Denote the RPLs between n & CO_m as $\Phi_{n,m}^{\text{sp}}(t) = \sum_{k\in CO_m, n\neq k} \phi_{n,k}(t)$. Then, we take $U_m\left(G_{\text{st}_m,\text{st}-m}\right) = \Phi_{m,s\ t_m'^+}(t) + \Phi_{m,s\ t_m'^-}(t)$ as the edge in the action graph. Note that there exists an upper bound for O-EDM rate, we adopt the best response (BR) method.

Firstly, determine the stage of GSs as Lv.1, says m^*. Then, select the coalition farthest from m^*, say m_1; Next, select the nearest coalition of m_1, say m_2 as its subordinate coalition. Finally, we obtain optimal $U_{m_1}(\cdot)$, and $\varepsilon_{m_1,m_2} = 1$. We then exclude coalition m_1 and continue above cycles until all coalitions are connected.

Next, we present selection mechanism of ND set $\mathcal{B}$. Denote the O-EDM rate from n to coalition $m_1 \& m_2$ as:

$$\psi_{m_1,m_2}^n(t) = (\Phi_{n,m_1}^{\text{sp}}(t) + \Phi_{n,m_2}^{\text{sp}}(t))/(\Phi_{n,m_1}^{\text{cmp}}(t) + \Phi_{n,m_2}^{\text{cmp}}(t)). \tag{8}$$

We similarly used BR to find the best four CUs (using sort function in Matlab) that maximize the O-EDM rate as NDs. After adjusting the ND sets, the trend of changing value in $V(CO, \Pi)$ is the same as in $\psi_{m_1,m_2}^n(t)$.

Remark 2: Under the proposed feasible local strategy in Algorithm. 1, the CGG $\mathcal{G}_2$ is proven to be a local Nash network. Generally, pairwise stability exists, which indicates that $\mathcal{G}_2$ can achieve a stable state. That is, no CU can improve its O-EDM rate through adjusting strategy.

C. Localization Algorithm Design

Based on Algorithm. 1, we design a multistage clustering-based UAV localization algorithm (CG- Tree Loc

Algorithm 1: CG-Based Tree-Like Multistage Algo

Input : $\boldsymbol{\Theta}$, Π, $\mathcal{M}$, $j = 1$, maximal iteration time J.

1 // ***Synchronization***
2 **while** *$j \leq J$ or the stop criterion is met* **do**
3 Randomly select CU n;
4 $\left\{CO_{c_n}^*, CO_{c_k}^*\right\} \leftarrow \left\{CO_{c_n} \setminus \{n\}, CO_{c_k} \cup \{n\}\right\}$;
5 $\Pi^* \leftarrow \Pi \setminus \left\{CO_{c_n}, CO_{c_k}\right\} \cup \left\{CO_{c_n}^*, CO_{c_k}^*\right\}$; // ***CSR***
6 // ***Tree − likeStructureFormation***
7 set $\mathcal{M}^* = \emptyset$, $m^* = c_{N+1}$;
8 **while** $\mathcal{M}^* \neq \mathcal{M}$ **do**
9 $m_1 \leftarrow \arg\min_{m_1 \notin \mathcal{M}^*} \Phi_{m^*,m_1}$; // ***BR***
10 $\mathcal{M}^* \leftarrow \mathcal{M}^* \cup m_1$;
11 $m_2 \leftarrow \arg\max_{m_2 \in \mathcal{M}^*} \Phi_{m_1,m_2}$; // ***BR***
12 $\varepsilon_{m_1,m_2} = 1$;
13 $\psi_1 \leftarrow \text{sort}(\psi_{m_1,m_2}^n, -2)$;
14 $\mathcal{B}_{m_1,m_2} \leftarrow \psi_1(1:4, 1)$; // ***NDSet***, (8)
15 $c_n \leftarrow [m_1, m_2], n \in \mathcal{B}_{m_1,m_2}$;
16 $st_m, st_m^+, st_m^- \leftarrow \mathcal{B}_{m_1,m_2}$
17 **end**
18 Calculate $V(CO_{c_n}, \Pi)$, $V(CO_{c_n}^*, \Pi^*)$, $V(CO_{c_k}, \Pi^*)$ & $V(CO_{c_k}^*, \Pi^*)$ **if** *Update condition is met based on* (7) **then**
19 $\Pi \leftarrow \Pi^*$; // ***CoalitionUpdate***
20 **end**
21 $j = j + 1$
22 **end**

Output : $\{c_n\}_{n\in\mathcal{N}}$, Π, $\left\{st_m, st_m^+, st_m^-\right\}_{m\in\mathcal{M}}$

Algorithm 2: Multistage Clustering-Based UAV Localization Algo (CG-Tree Loc Algo)

Input : $\boldsymbol{\Theta}$, Π, $\mathcal{M}$, $\{\mathbf{p}_n\}_{n\in\{\mathcal{N}_1\cup\mathcal{N}\}}$.

// ***Synchronization***

Enter Algorithm. 1 and obtain $\{c_n\}_{n\in\mathcal{N}}$, Π, $\mathcal{B}_m$;

// ***Clustering − based Localization***

for $m = 1$ *to* M **do**

  $\mathbf{H}_m \overset{\text{ALS-MC}}{\longleftarrow} \mathbf{H}_m^{\circ}$; Get CO m's stage l;

  if $l == 1$ **then**

    GS-based Local Coordinate System Construction [5]

  else

$$\left.\begin{array}{l}\mathbf{H} \leftarrow -\frac{1}{2}\cdot\mathbf{J}\hat{\mathbf{H}}_m\mathbf{J}, \mathbf{J} \leftarrow \mathbf{I}_{N_1} - \mathbf{1}_{N_1}\mathbf{1}_{N_1}^T/N_1 \\ [\mathbf{U},\mathbf{S},\mathbf{V}] \leftarrow \mathrm{SVD}(\mathbf{H}), \hat{\mathbf{X}} \leftarrow \mathbf{V}\mathbf{S}^{\frac{1}{2}} \\ \{\mathbf{p}_n^{\text{ret}}\}_{n\in\mathcal{N}_2} \leftarrow \hat{\mathbf{X}}(1:3,:)\end{array}\right\}\textbf{MDS;}$$

$$\left.\begin{array}{l}\{b,\mathbf{T},\mathbf{c}\} \leftarrow \left(\mathbf{p}_k^{l-1} \xrightarrow{\text{LT}} \mathbf{p}_k^{\text{ret}}\right), k\in\mathcal{B}_m \\ \{\mathbf{p}_n^{l}\}_{n\in\mathcal{N}_2} \overset{\{b,\mathbf{T},\mathbf{c}\}}{\longleftarrow} \{\mathbf{p}_n^{\text{ret}}\}_{n\in\mathcal{N}_2}\end{array}\right\}\textbf{Map Fusion}$$

  end

end

// **Data Processing**

Output : $\{\mathbf{p}_n\}_{n\in\mathcal{N}_2}$.

Algo, as shown in Algorithm. 2), which mainly includes : **1) Synchronization:** CUs broadcast through communication links and transmit SNR matrix $\boldsymbol{\Theta}$ to GS_1. **2) Clustering-based Localization:** GS_1 executes Algorithm 2 and calculate position results. **3) Data Processing:** GS_1 transmit them back to the swarm. In the algorithm, denote $\mathbf{p}_n^l$ as the CU n's position in the l_{th} stage.

Next, we give the complexity analysis of the algorithm. For Algorithm. 2, since the sort function requires traversing all coalition, the computation complexity for each time slot j is $\mathcal{O}\left(M^2\right)$; Clustering reduces the time complexity of MDS-MAP, which is $\mathcal{O}\left(N^{ave}\cdot N^2\right)$, where $\bar{N}$ is the average number of nodes in each clustering. Besides, denote $\mathcal{O}\left(Rec\right)$ as the computation complexity for recording data each time slot. Thus, the total computational complexity of the proposed CG- Tree Loc Algo is calculated as:

$$\mathcal{T}_{\text{comp}} = J\cdot\left[\mathcal{O}\left(M^2\right) + \mathcal{O}\left(M\cdot\bar{N}^2\right) + \mathcal{O}\left(Rec\right)\right]. \quad (9)$$

Compared to the first two items, $\mathcal{O}(Rec)$ are small constants.

IV. Simulation Results & Discussion

In this section, we carry out simulations (in Matlab R2019b) to verify the convergence and localization performance of the proposed algorithm. The mission area is located at a 3-D space (Border: $L_{\text{lg}}\times L_{\text{wd}}\times L_{\text{he}}$ m, $N = 50, N_2 = 52$), in which CUs are randomly deployed. Set GSs' position as $\mathbf{p}_{N_1} = [0, L_{\text{wd}}/2, 0]$ (m) and $\mathbf{p}_{N_2} = [L_{\text{lg}}/5, L_{\text{wd}}/2, 0]$ (m). Based on UWB localization, we set threshold $\eta_{\min} = 1.2$, the bandwidth $B_c = 500$ MHz. ε_t^1 & ε_t^2 follows Rayleigh fading. Other parameters $G = 1$, $\alpha = 3$, $N_0 = -174$ dB/Hz. The simulation variables are: $M = 3 \sim 8$, $\mathrm{Pt}_n = -14.3 \sim -8.3$ dbm, $L_{\text{lg}} = L_{\text{wd}} = 70$ m ~ 600 m, $L_{\text{he}} = 15$ m ~ 45 m. We set border ratio $L_{\text{lg}}/L_{\text{wd}}$ to characterize the network topology.

Root mean squard error (RMSE) and localization success rate (LocSR) are adopted to characterize the localization performance metrics. Given measurement results $\mathbf{p}_n$ and the true position value $\hat{\mathbf{p}}_n$, RMSE(m) $= \sqrt{\frac{1}{N}\sum_{n=1}^{N}\|\mathbf{p}_n - \hat{\mathbf{p}}_n\|^2}$;

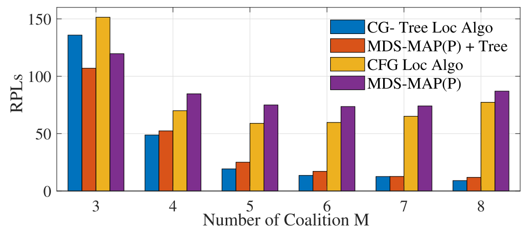


Fig. 2. Statistical analysis of RPL considering coalition amounts.

e_{th} is the maximum error allowed for successful localization, then LocSR(%)(m) $= \mathcal{N}_{\text{succ}} = \{n\in\mathcal{N}|\,\|\mathbf{p}_n - \hat{\mathbf{p}}_n\| < e_{\text{th}}\}$. We set $e_{\text{th}} = 5$ m in the simulation.

Our simulation introduces MDS-MAP (P) [1] and CFG-based Localization [5] (abbreviated as CFG Loc Algo) as comparison algorithms. Besides, we add multistage clustering mechanism to MDS-MAP (P) (abbreviated as MDS-MAP (P) + tree). Finally, global localization is introduced. All algorithms adopt the matrix completion method from [5]. While ensuring the invariants of the comparison algorithms are maintained, we rerun all the algorithms 100 times to simulate different network topologies and take the average results.

A. Performance Comparisons Considering the Number of Coalitions

In order to compare the impact of the number of coalitions M to the algorithms, we deploy a $340\text{ m}\times 340\text{ m}\times 45\text{ m}$ mission area, where $L_{\text{lg}}/L_{\text{wd}} = 1$ to avoid the influence of network topology. Then, we set CUs' transmit power Pt $= -14.3$ dBm). The results are shown in Figure. 2. When $M = 3$, the number of coalitions is insufficient, resulting in a poor clustering effect for all algorithms. As M increases, the RPLs of all clustering algorithms show a downward trend and gradually slow down ($3 \le M \le 6$), which verifies that clustering can effectively alleviate RPLs. When $M \ge 7$, RPLs approach the performance lower bound. RPLs of comparison algorithms even become larger due to excessive strategy selections. Compared with MDS-MAP (P) + Tree, the proposed algorithm reduces RPLS by 12.3% on average. Set $M = 5$, Figure. 3 shows a diagram for CG-Tree Loc Algo. All CUs are divided into five clusters. CO_1 is set to be the first stage (Lv. 1). Map fusion is performed through NDs & CO_2 (CO_3) in Lv. 2; Similarly, CO_2 (CO_3) performs map fusion through NDs & CO_4 (CO_5) in Lv. 3, which is in accord with the proposed multistage clustering-based model.

B. Performance Comparisons Considering Transmit Power

We set border ratio $L_{\text{lg}}/L_{\text{wd}} = 4$, where the border is $620\text{ m}\times 155\text{ m}\times 45\text{ m}$ mission area. Figure. 4 presents the performance curve. As Pt increases, RMSE of all algorithms decrease, while LocSR increase. Table. I shows that the proposed algorithm achieves the lowest RMSE (2.71m) and the highest LocSR (96.7%) in average. Furthermore, the proposed algorithm achieves better localization performance than MDS-MAP(P) + Tree, demonstrating the CFG-based clustering scheme's advantages in alleviating RPLs.

C. Performance Comparisons Considering Border Ratio

This part investigates the algorithm performances under different network topologies. The parameters are as follows:

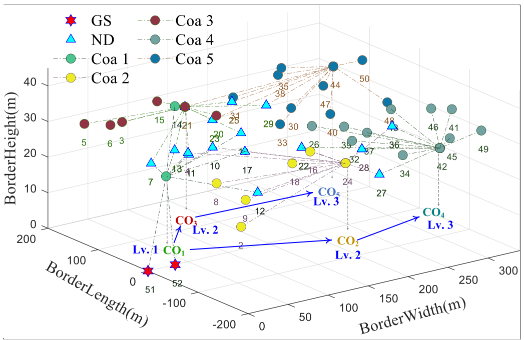


Fig. 3. One simulation diagram for CG-Tree Loc Algo.

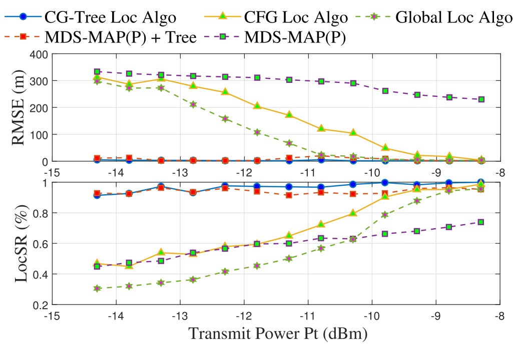


Fig. 4. Performance comparisons under different algorithms considering transmit power (620 m $\times$ 155 m $\times$ 45 m, $M = 5$).

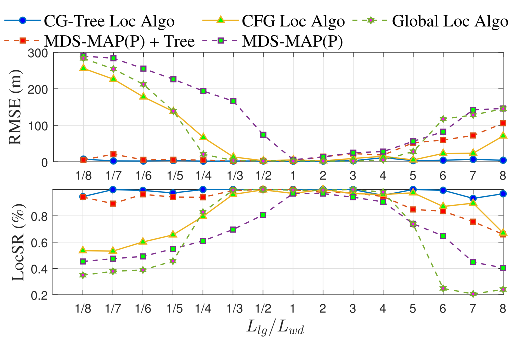


Fig. 5. Performance comparisons under different algorithms considering Border Ratio ($\mathrm{Pt}_n = -14.3$ dbm, $L_{\mathrm{lg}} \times L_{\mathrm{wd}} = 100000\ \mathrm{m}^2$, $M = 5$).

TABLE I

STATISTICAL ANALYSIS OF LOCALIZATION PERFORMANCE IN AVERAGE WITH A) $\mathrm{Pt}_n = -14.3 \sim -8.3$ dBm; B) BORDER RATIO $L_{\mathrm{lg}}/L_{\mathrm{wd}}$

A) \ Algorithm	**RMSE (m)**	**up↑(m)**	**LocSR (%)**	**up↑(%)**	**RPL**
CG- Tree Loc Algo	2.71	108.5	96.7	39.4	4.5
MDS-MAP(P) + Tree	7.24	103.96	94.1	36.8	4.0
CFG Loc Algo	163.8	-52.6	70.1	12.8	55.5
MDS-MAP(P)	291.4	-180.2	59.7	2.4	81.6
Global	111.2	/	57.3	/	522.4
B) \ Algorithm	**RMSE (m)**	**up↑(m)**	**LocSR (%)**	**up↑(%)**	**RPL**
CG- Tree Loc Algo	3.9	85.8	98.4	33.1	2.1
MDS-MAP(P) + Tree	26.3	63.4	91.2	25.9	9.3
CFG Loc Algo	69.1	20.6	82.7	17.4	30.4
MDS-MAP(P)	132.5	-42.8	67.4	2.1	51.5
Global	89.7	/	65.3	/	450.4

border ratio $L_{\mathrm{lg}} \times L_{\mathrm{wd}} = 100000\ \mathrm{m}^2$, mission area is $L_{\mathrm{lg}} \times L_{\mathrm{wd}} \times 45$ m, CUs' transmit power $\mathrm{Pt}_n = -14.3$ dBm. From Figure. 5, as $L_{\mathrm{lg}}/L_{\mathrm{wd}}$ gradually deviated from 1:1, the RMSE of all comparison algorithms has increased, and the LocSR has also decreased. As the border ratio $L_{\mathrm{lg}}/L_{\mathrm{wd}}$ deviates farther from 1:1, the worse the localization performance is. We analyze that the border ratio directly reflects and affects the network topology, and comparison algorithms have poor performance when facing irregular network topology. It is worth mentioning that CG-Tree Loc Algo can consistently maintain the robust localization performance. Statistical results (Table. I) also shows that the CG- Tree Loc Algo can complete the cooperative localization under different network topologies and CUs deployment in the given scenario. Thus, the simulation results confirm the effectiveness and robustness of the proposed multistage clustering-based localization.

V. CONCLUSION

This letter constructed a multistage clustering-based model for remote UAV swarm. ADS-TWR was adopted for ranging. Each cluster (local map) performs localization calculation and then merges through NDs stage by stage. We characterized the proposed model as a coalitional game and designed a tree-like multistage clustering scheme. Simulation results evaluated the effectiveness of the proposed coalitional game (CG) framework. The proposed CG-Tree Loc Algo effectively alleviates RPLs, achieves lower RMSE and higher LocSR than the comparison algorithms, and was robust for irregular network topologies. Our work has proved advantageous for remote localization and robust for dynamically changing network topologies. The proposed CG framework offers novel thoughts for other TOF-based localization approaches.

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