

A Survey of UAV Clustering Algorithm

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Abstract— As a rapidly developing emerging technology, unmanned aerial vehicles (UAVs) have attracted widespread attention in academic research, military applications, and civilian use. Close collaboration among multiple UAVs to form UAV clusters can be used to accomplish various missions in complex and unique environments. Therefore, it is gradually becoming an essential form of current UAV combat applications. However, the high mobility, frequent topology changes, and limited energy of UAVs bring challenges to the communication design of UAVs, and how to manage them to work efficiently has become a problem to be solved in UAV clusters. The extant literature shows that the above problems can be solved by an effective clustering approach, thus effectively improving the performance of large-scale UAV clusters. This paper first introduces different existing clustering algorithms in UAV clusters, then provides a comparative analysis of the different clustering algorithms, and finally, discusses future research directions for clustering algorithms in UAV cluster communication.

Keywords— FANET; UAV cluster; clustering; cluster head selection; routing

I. INTRODUCTION

In recent years, with the increasingly widespread application of UAVs, communication among UAVs has gradually become a hot content of current research. Compared with single UAV communication, multiple UAVs can collaborate more effectively to accomplish complex tasks. Multi-UAV networks are often referred to as flying ad hoc networks (FANET). In a FANET, all UAVs establish an ad hoc network, and only a subset of the UAVs connect to the infrastructure; the others use intermediate UAVs to communicate with the ground controller in a multi-hop way[1]. FANET is widely used in many fields, such as emergency networks[2], battlefield applications, object tracking[3], timely recovery services after natural disasters, wildfire detection and surveillance, relay for ad hoc networks, delivery service [4], search and rescue operations[5], and other fields.

With the gradual increase in the scale of UAVs, resource allocation and routing among UAVs are facing particular challenges. Dividing UAVs into clusters for hierarchical management is an effective solution. Controlling the network through clustering has a good effect in solving the heterogeneity of nodes, enhancing the fault tolerance and scalability of the network. In the clustering approach, as shown in Figure 1. Each UAV can be seen as a node, and the UAV nodes are divided into

different clusters. Within the effective communication range of the nodes, these UAV nodes can communicate directly with each other, sharing channels and resources. Each cluster chooses a cluster head (CH) that is responsible for managing inter-cluster and intra-cluster communication. The remaining UAVs within a cluster are called cluster members (CMs). Suitable cluster head selection strategy and efficient cluster management can reduce communication overhead, enhance network scalability, and maximize network throughput.

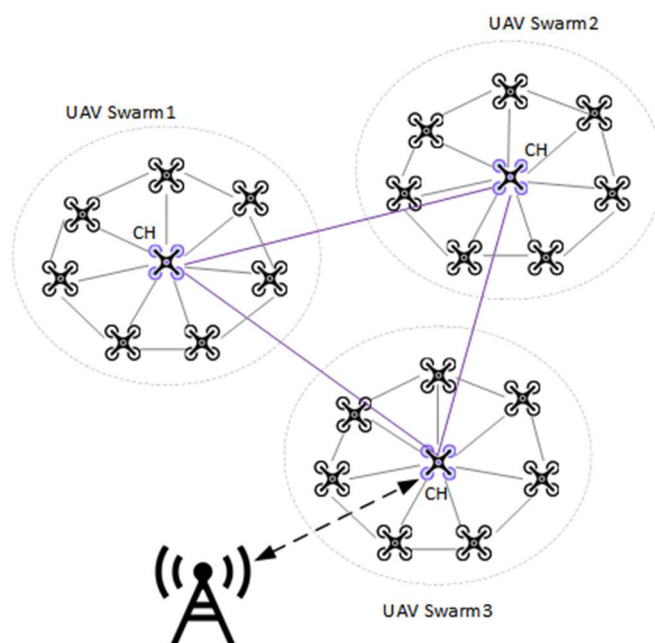


Figure 1. UAV cluster division example diagram.

Unlike vehicular ad hoc network (VANET) or mobile ad hoc network (MANET), FANET has the unique features of high mobility, frequent topology changes, unstable wireless links, and limited energy resources. Therefore, this brings challenges to reliable communication and routing among UAVs. The main challenges faced by FANET are reflected in 1) Since UAVs carry limited battery energy, it is essential to consider how to effectively use node energy for efficient work when UAV clusters work together. 2) The characteristics of UAVs, such as high mobility and frequent network topology changes, may lead to interruption of UAV links and impair link quality, thus affecting the reliability of the network and increasing overhead,

packet loss rate, and delay. 3) The high mobility of UAVs, frequent topology changes, link instability, and limited energy bring challenges to the UAV positioning problem. The above problems can be better solved by clustering management of UAVs.

The rest of this paper is organized as follows. In the next section, existing protocols for cluster-based clustering algorithms in UAV communication are presented. In Section III, different clustering algorithms are compared. In Section IV, the next research directions of clustering algorithms in UAV clusters are discussed and summarized in the full paper.

II. RELATED WORK

In this paper, we focus on the perspective of the problems to be solved in UAV network communication, which are divided into the following four categories: 1) based on energy consumption 2) based on mobility 3) based on Energy Consumption and Mobility 4) based on localization, as shown in Figure 2. This section describes the specific ideas of each algorithm and introduces the application scenarios for which each type of algorithm is suitable.

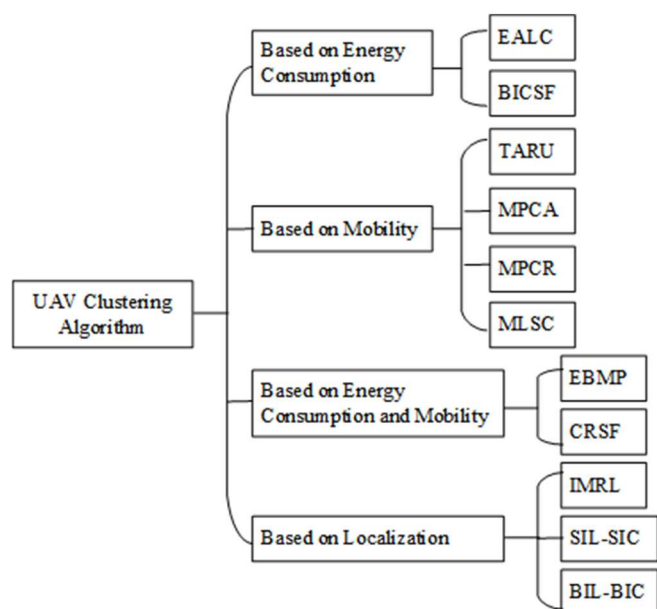


Figure 2. Classification of UAV clustering algorithms.

A. Based on Energy Consumption

Raza, A. et al. [6] proposed the Energy Aware Link-based Clustering (EALC) model. EALC uses K-means density clustering algorithm to select cluster heads. The optimal cluster head is selected considering the node energy level and distance to neighbors, and the number of clusters is sized by the communication range of the cluster head, improving the cluster lifetime and reducing the overhead. When the cluster head's fitness value (Calculated by node energy level and distance) is lower than the set threshold level, the cluster maintenance strategy is invoked. Compared with the schemes based on Ant Colony Optimization-based (ACO) clustering algorithm and Grey Wolf Optimization-based (GWO) clustering algorithm, this scheme improves the lifetime of UAVs through effective

clustering. However, it does not apply to very high mobility UAV nodes. Therefore, optimization improvements can be considered by introducing a mobility prediction mechanism for efficient routing of very high mobility UAVs.

For the problem of unstable routing due to limited energy resources and mobility of UAVs, a bio-inspired clustering scheme for FANETs (BICSF) based on a hybrid mechanism of glowworm swarm optimization (GSO) and krill herd (KH) is proposed in the literature [7]. BICSF uses GSO algorithms to elect cluster heads based on the UAVs' residual energy and luciferin level and KH intelligent algorithm to management clusters efficiently. For inter-cluster communication, path selection is performed based on weighted residual energy, number of neighbors, and distance between UAVs for efficient communication. For cluster maintenance, the CH sets a threshold energy level to achieve efficient cluster maintenance by monitoring the energy level of UAVs in the cluster. Compared with the ACO and the GWO algorithm, the BICSF algorithm converges quickly to the optimal solution. Therefore, it saves the energy consumption of UAVs during complex computation and makes the cluster build time shorter and cluster lifetime longer. However, not considering the connectivity of nodes during cluster head selection can lead to an excessive number of cluster heads, and the energy consumption may increase.

For the above-mentioned clustering-based routing protocols that solve the energy consumption problem, all consider the energy level of UAVs in CH selection and UAV routing because CHs need to maintain inter-cluster and intra-cluster communication, their energy consumption is higher than CM UAVs. CHs with a long survival period can avoid frequent cluster reconfiguration, reduce unnecessary overheads and lower network energy consumption. This type of clustered routing protocol is adapted to scenarios with low mobility and the need to work for long periods, such as reconnaissance and monitoring tasks.

B. Based on Mobility

The high mobility of UAVs leads to frequent network topology changes. For routing to adapt to topology changes quickly, a topology-aware routing scheme (TARU) for UAV swarms is proposed in the literature [8], which first calculates the link duration based on the formation state and topology-related information. It then dynamically adjusts the hello interval and link hold timer according to the value of the link duration. This scheme reduces the average delay and improves routing performance. However, the hello message overhead increases when neighbor relationships change frequently, and therefore needs to be improved when applied to scenarios with frequent topology changes.

Zang, C., and S. Zang.[9] proposed a mobility prediction clustering algorithm (MPCA) relying on the attributes of UAV, which predicts topology changes based on link expiration time (LET) mobility prediction model and dictionary Trie structure (DTS) prediction algorithm to minimize cluster update speed. Then, the selection of cluster head is based on the weighted sum of link expiration time and DTS prediction schemes. The

algorithm can be applied to highly dynamic FANETs since the high mobility of UAVs is taken into account.

Shu, J., et al. [10] proposed a Mobility Predictive Clustering Routing (MPCR) algorithm that selects the node with maximum connectivity as cluster head and introduces ferry nodes to forward packets to the host of disconnected clusters. MPCR has better results in terms of delay and data delivery. However, this scheme does not consider the energy level of the nodes when selecting cluster heads, so it does not apply to UAVs with small battery capacity.

A Mobility and Location-aware Stable Clustering (MLSC) mechanism is proposed in the literature [11]. The mobility and relative location of UAVs are considered in MLSC to improve the performance and reliability of UAV networks with limited resources. First, the optimal cluster size is found based on the maximum coverage probability of the cluster head to minimize the network overhead, and then a distance-based k-means clustering algorithm is used to select the stable cluster head at the optimal location required. All CHs and sinks are connected using an approximate Minimum Spanning Tree (MST) algorithm to construct the backbone routing tree. Finally, an active backup cluster head scheme is introduced to achieve the CH location when the current cluster head exits or leaves the network, maintaining the stability of the clustered network. Compared with traditional clustering methods, this algorithm significantly reduces the network overhead and latency and improves the packet delivery rate. However, this scheme does not consider the energy level when selecting cluster head UAV, so clusters may require frequent maintenance; the MLSC cluster head selection algorithm can be optimized by considering energy level factors.

The clustering routing protocols as mentioned above, which are proposed to address the problems of frequent network topology changes and link instability caused by high mobility of UAV, basically take into account factors such as node connectivity and link duration when clustering and routing and perform well in terms of PDR and EDET performance. This type of protocol is suitable for delay-sensitive scenarios, such as transmitting audio and video data during the rescue.

C. Based on Energy Consumption and Mobility

Fang, et al. [12] proposed an energy balance and mobility prediction (EBMP) clustering algorithm. During the cluster formation phase, the energy consumption of the UAV (E_i) and the stability of the UAV (SD_i) are obtained by the proposed energy consumption model and the movement prediction model, and the weight of each UAV is calculated according to Equation (1), so that the UAV with the largest weight is selected as the CH UAV; in the cluster maintenance phase, it uses CH rotation strategy to maintain the stability of the cluster; in the communication phase, the intra-cluster communicates directly, and the inter-cluster communicates through a gateway (selected using the shortest distance projection method). Compared to MPBC and MPCR algorithms, the EBMP algorithm can achieve a longer average CH lifetime, better throughput, and lower average latency.

$$Weight_i = 0.26e^{-E_i} + 0.74e^{-SD_i} \quad (1)$$

where 0.26 and 0.74 were determined by the Analytic Hierarchy Process (AHP). E_i is the energy consumption of the UAV i and SD_i is the relative stability of the UAV i .

To address the communication problems caused by the mobility of UAVs, Khan, et al. [13] proposed an intelligent cluster routing scheme for flying ad hoc networks (CRSF). Specific scheme: Cluster heads are selected using the adaptive value calculated by Equation (2) based on the position and residual energy of the UAV and the one with the highest adaptive value is selected as the cluster head. A cluster management mechanism inspired by Moth Flame Optimization (MFO) is proposed to manage UAV clusters effectively. In CRSF, a detailed cluster head reselection mechanism is proposed in order to maintain cluster stability, which helps to maintain clusters for effective topology management. Once the cluster is formed, to achieve efficient routing and load balancing in FANET, a routing mechanism for UAV communication is proposed for CRSF to send data to the destination UAV, selecting the next-hop route by considering the Euclidean distance and the remaining energy. MATLAB simulation results show that CRSF has better performance in energy consumption, cluster survival, throughput and PDR than BISCF and ACO.

$$Fitness = (w_1 \times f_1) + (w_2 \times f_2) \quad \text{where } w_1 + w_2 = 1 \quad (2)$$

where w_1 and w_2 are the weights of the parameters, taking a fixed equal value of 0.5, which is more helpful for selecting UAVs with better adaptation. f_1 is the position of the UAV and f_2 is the residual energy of the UAV.

This type of clustered routing protocol considers both the high mobility and energy consumption of UAVs, and its CH selection takes into account energy and node degree to make the cluster survive longer. This protocol performs better in network energy consumption, throughput, and latency and is suitable for application scenarios requiring extended working hours and low latency.

D. Based on Localization

A Data Routing Scheme based on Localization and Energy-Efficient is proposed in the literature [14]. The specific scheme is based on the received signal strength indication (RSSI) values between the UAV and the anchor node using weighted centroid localization technique and fuzzy logic (FL) inference to calculate the unknown UAV node's position improves the localization accuracy. Then, the cluster head selection is based on the remaining energy, the distance between nodes and neighboring cluster heads, and the distance between cluster heads and sink nodes to minimize the energy consumption of the whole network, thus extending the cluster lifetime.

M. Y., and S. Moh. [15] proposed a swarm intelligent localization (SIL) algorithm based on particle swarm optimization (PSO). SIL uses the bounding box method to reduce the initial search space and improve the algorithm's convergence capability and speed. The algorithm estimates the location of the target UAV node by measuring the distance of the existing anchor node, which has lower localization error and higher localization accuracy. An energy-efficient swarm intelligent clustering (SIC) algorithm based on particle swarm

algorithm is also proposed, which considers location information, inter-cluster distance, intra-cluster distance, and residual energy to cluster and select cluster heads of nodes. The

algorithm minimizes the network energy consumption and extends the network lifetime.

TABLE 1. CLUSTER-BASED ROUTING PROTOCOLS - SUMMARY

Protocols	Based on the algorithm	Selection of cluster head	Cluster maintenance	Routing Metric	Strength	Weakness
EALC [6]	K-Means Density clustering algorithm	The fitness value calculated by the node energy and the distance	Set threshold	Energy level and distance	Lower cluster build time and energy consumption compared to ACO and GWO based solutions	Only considered drones with moderate mobility
BICSF [7]	GSO	The fitness value calculated by residual energy and luciferin level	Define threshold energy level	Path detection function based on weighted remaining energy, number of neighbours, and distance	Performs well in terms of cluster construction time, energy consumption, cluster lifetime, and data packet delivery rate	UAV connectivity was not considered when selecting cluster heads
TARU [8]	-	-	Set the link holding timer	Node's link duration	Reduced average delay and significantly improved routing performance	When neighbours change frequently, HELLO packet overhead will increase
MPCA [9]	DTS algorithm and LET mobility model	The weighted sum of LET and DTS	On-demand maintenance	LET and connectivity degree	Better stability of the cluster structure	Number of cluster heads increases sharply with cluster members
MPCR [10]	-	Connectivity	-	Connectivity degree	Higher PDR and lower ETED	Energy consumption problem
MLSC [11]	K-Means distance clustering algorithm	Distance	Backup cluster head scheme	MST algorithm	Reduced network overhead, improved PDR and network latency	Energy is not considered in cluster head selection
EBMP [12]	-	Energy consumption and the relative stability degree of each UAV	CH rotations	Energy consumption, distance	Energy consumption in the whole network more balanced, and the structure of clusters trends stable	Cluster maintenance overhead increases in high mobility scenarios
CRSF [13]	MFO	Position and UAVs' residual energy	CH re-selection mechanism	The route identification function based on the Euclidean distance and residual energy	Lower complexity and better performance than other bio-inspired mechanisms	Not suitable for scenarios with sparse node distribution, computational complexity will increase
IMRL [14]	-	The node with the largest remaining energy	-	Function based on weighted CH remaining energy, distance	Superior to existing solutions in terms of positioning accuracy, positioning time, energy consumption and data transmission	No cluster maintenance strategy
SIL-SIC [15]	PSO	Fitness value calculated based on the distance and node residual energy	-	Function based on weighted residual energy, distance from CS, node degree	Higher positioning accuracy; superior to typical routing protocols in terms of PDR, ETED, and routing overhead	Positioning is not applicable to high-speed UAV nodes
BIL-BIC [16]	HGWO	Residual energy of nodes, number of neighbours, distance within clusters	-	Adopt CS-GWO scheme routing	Higher positioning accuracy, faster convergence speed; low energy consumption, high data transmission efficiency, and network reliability	No cluster maintenance strategy

In the literature [16], M. Y., and S. Moh proposed another a bio-inspired localization (BIL) algorithm that uses the bounding cube approach to reduce the initial search space and the hybrid gray wolf optimization (HGWO) algorithm to determine the actual location of unknown nodes. This algorithm reduces the computational cost while improving the localization accuracy. Bio-inspired clustering (BIC) algorithm is also proposed, and BIC uses HGWO to optimize cluster formation and cluster head selection. It reduces the energy consumption by considering various issues such as the number of clusters, cluster size, cluster stability, and the number of transmissions. Finally, the GWO-based compressive sensing (CS-GWO) algorithm is proposed for data transmission, but it has limitations for monitoring wildfires in remote areas because the nodes are far away from the base station (BS) the BS is not in the transmission range of the nodes. Optimization using multiple antennas can be considered in the future.

The localization method proposed by those as mentioned earlier clustered routing protocols improves the accuracy of localization, and the CH selection is based on more accurate location information at the time of clustering, and the next-hop route is selected at the time of communication considering the distance, with lower localization error and better performance in terms of energy consumption and PDR. This type of protocol is suitable for scenarios with high localization requirements, such as post-disaster search and rescue.

Different protocols for clustering routing algorithms are proposed for different problems, such as reducing the energy consumption of UAVs, maintaining the stability of cluster

structure, and obtaining accurate location information of UAVs. Table 1 summarizes and compares the protocols described above in terms of the algorithms on which they are based, the basis for CH selection, cluster maintenance strategies, routing metrics, and strengths and weaknesses.

III.COMPARISON

The following Table 2 shows the comparison of existing clustering algorithms in the different parameters like Cluster build time, cluster lifetime, Energy consumption, packet delivery ratio (PDR), and End-to-end delay (ETED).

1) Cluster building time: The time taken to execute the clustering algorithm to form clusters and cluster head selection is called cluster building time, which represents the computational complexity of that algorithm. The shorter the build time, the lower the energy consumption.

2) Cluster lifetime: The time between cluster formation and cluster destruction. The longer the cluster lifetime, the fewer the number of cluster reconfigurations.

3) Energy consumption: The energy consumption of the entire network to execute the clustering algorithm with other algorithms.

4) ETED: The time difference between sending packets to the destination, the lower the delay, the better the performance.

5) PDR: The ratio of the total packets received by the destination node to the total packets sent by the source node.

TABLE 2. COMPARISON OF THE EXISTING CLUSTERING ALGORITHM

Algorithm	Cluster build time	Cluster lifetime	Energy consumption	ETED	PDR	Comparison algorithm	Simulator
EALC [6]	short	long	low	-	-	CACONET, GWOCNET	MATLAB
BICSF [7]	short	moderate	low	-	-	EALC [16]	MATLAB
TARU [8]	-	-	-	low	high	OLSR	QualNet
MPCA [9]	long	short	high	-	-	EALC [16]	NS2
MPCR [10]	-	-	-	low	high	AFNC, SF	-
MLSC [11]	-	-	-	low	high	ACO, GWO	MATLAB
EBMP [12]	-	long	-	low	-	MPBC, MPCR	NS-2.29 and MATLAB
CRSF [13]	-	long	low	-	high	BICSF, ACO	MATLAB
IMRL [14]	-	-	low	-	high	EMHR, BeeCluster	MATLAB
SIL-SIC [15]	short	long	low	low	high	EALC	MATLAB
BIL-BIC [16]	short	long	low	-	-	EALC	MATLAB

IV.CONCLUSIONS

In the future, large-scale UAV clustering is a significant development direction, and the resource management and network performance of UAV clusters can be improved through clustering, but due to some unique characteristics of UAVs, the existing clustering-based routing protocols for traditional MANET and VANET cannot be directly applied to UAV self-assembly networks, so the cluster management of large-scale unmanned self-assembly networks needs further optimization research.

In the future, (1) artificial intelligence can be considered to be applied to the clustering algorithm of UAVs, such as

optimizing the formation of clusters and the selection of cluster heads, and achieving high-speed node localization, in order to make the clusters lifetime longer and the network as a whole consume less energy and perform better. (2) Intelligent UAV clusters based on the intelligent behavior of biological swarms. Swarm intelligence stems from the study of the swarm behavior of social insects represented by ants, bees, and others. The swarm behavior of animal groups for cooperative foraging maximizes the interests of the group. Inspired by the intelligent behavior of biological swarm in nature, it can be used to achieve intelligent inter-cluster and intra-cluster control of UAV clusters. At the same time, the biological swarm intelligence optimization algorithm has good scalability, strong

robustness, and self-organization. It can be used to solve optimization problems in UAV clusters, such as optimizing the division of clusters, selecting cluster heads, and managing clusters.

This paper summarizes and compares the current work on large-scale UAV clusters and discusses the open problems and following research directions for large-scale UAV cluster communication.

Abbreviations

Acronym	Definition
UAVs	Unmanned Aerial Vehicles
FANET	Flying Ad Hoc Network
CH	Cluster Head
CMs	Cluster Members
VANET	Vehicular Ad Hoc Network
MANET	Mobile Ad Hoc Network
ACO	Ant Colony Optimization
GWO	Grey Wolf Optimization
KH	Krill Herd
DTS	Dictionary Trie Structure
LET	Link Expiration Time
MST	Minimum Spanning Tree
RSSI	Received Signal Strength Indication
MFO	Moth Flame Optimization
FL	Fuzzy Logic
PSO	Particle Swarm Optimization
HGWO	Hybrid Gray Wolf Optimization
CS-GWO	GWO-based Compressive Sensing
BS	Base Station
PDR	Packet Delivery Ratio
ETED	End-to-end Delay

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