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Optimal Routing For Beamforming-Constrained Swarm UAS Networking

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Abstract—With the evolution of 5G cellular communication, beamforming is mature for the implementation on a large scale. The development of cellular networking provides a great opportunity for swarm UAS. Concurrently, the advantages of swarm UAS can provide immense improvement to the advance of industrial and residential implementations. However, the nature of the antenna array constrains beamforming in a limited space which is rarely mentioned in networking routing researches.
In this paper, regarding the constrained steering space, we proposed a novel algorithm, Optimized Ad-hoc On-demand Distance Vector (OAODV), which aims to improve the capacity of beamforming on swarm UAS networking. With the adjustable searching space, OAODV can achieve better latency, overhead, and link generation than the conventional algorithms of Ad-hoc On-demand Distance Vector (AODV) and Optimized Link State Routing (OLSR). Compared with AODV and OLSR, OAODV can reduce 35.07% and 68.93% of average overhead, and decrease 47.73% and 11.55% of average latency respectively. Further, we leverage Ant Colony Optimization (ACO) to enhance OAODV, and the ACO enabled OAODV can achieve better throughput and fewer hops with reduction of overhead. The proposed algorithms show the promising capacity to improve swarm UAS networking.The OAODV is more suitable for the 5G cellular networking based swarm UAS networking. The decentralized advantages can improve the deployment of swarm UAS networking on a large scale with more efficiency, flexibility and elasticity.

Index Terms—Swarm UAS networking, Beamforming, Ant Colony Optimization, 5G cellular communication, Optimal Routing

1 Introduction

As cellular networking evolves, the 5th Generation New Radio (5G NR) is coming on a large scale. Compared with 4th Generation Long Term Evolution (4G LTE), 5G NR has more enhancements, such as latency [?], spectrum efficiency [?], traffic capacity [?], connection density [?], experienced throughput [?] and networking efficiency [?]. The implementations of 5G NR on a large scale are stimulating new revolutions in many fields like self-driving, health care, agriculture, education, etc [?], [?]. The advantages of 5G NR also drive the Unmanned Aircraft System (UAS) [?] feasible on a large scale. The advanced UAS helps workers, officials, and civilians to finish their work more efficiently and safely [?], [?]. Further, the capacity of UAS can be amplified remarkably once the UAS are formed in the swarm. The swarm UAS can execute multiple and complex missions simultaneously which improves the efficiency and the quality of mission complement [?]. As the core of swarm UAS, swarm UAS networking is critical to maintaining the performance of swarm UAS. And the capacity of swarm UAS networking is derived from the routing algorithms mostly [?]. Due to the cost of research and the limited swarm robot exploration, the routing algorithms for swarm UAS are rare. Most of the researches mainly focus on the capacity of the UAS fleet which is smaller than swarm UAS in the scale.

Currently, with the advance of 5G NR, beamforming is implemented to improve the UAS networking [?]. However, the conventional routing algorithms for UAS networking are mainly based on Ad-hoc On-demand Distance Vector (AODV) and Optimized Link State Routing (OLSR). AODV is decentralized, reactive, and less overhead for management which is robust to the dynamic topology. Nevertheless, the main drawbacks of AODV are the consumption of path discovery and the local optimization for routing generation [?], [?]. In contrast, OLSR is a centralized algorithm that could achieve global optimization of routing generation with the sacrifice of overhead [?]. Compatible with beamforming, a swarm-oriented routing algorithm, implemented with decentralization and efficiency, is an urgent need for the development of swarm UAS networking.

In this paper, we propose a swarm-oriented, decentralized, and efficient routing algorithm, Optimized Ad-hoc On-demand Distance Vector (OAODV), for swarm UAS networking. Based on beamforming, OAODV can select the next hops and deliver packets in directional. Each path discovery is labeled with the identified vector which allows OAODV to generate multiple paths to increase the routings and reduce the link generation and the latency. Most importantly, with the adjustable searching space, we can avoid unnecessary searching and reduce the overhead of swarm UAS. With the subjection to bandwidth and latency, Ant Colony Optimization (ACO) is implemented to contain better throughput and the fewer hops of routing. Compared with AODV and OLSR, OAODV shows promising potentials, which can reduce 35.07% and 68.93% of average overhead, and decrease 47.73% and 11.55% of average latency respectively. With the enhancement of ACO, the evaluation shows ACO enabled OAODV can reduce hops generation and increase throughput efficiently.

Different from the majority of research, we consider

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beamforming as a model with constraints for steering angles [?] which shows the maximum steering range is $0^\circ \sim 140^\circ$ with variation of $\pm 20^\circ$ currently. Most of the previous research ignored the constraints which will be a barrier to the implementation in practice. The most important effect of ignorance of the constraint of the steering angles can lose much energy on the unnecessary searching. Besides, the blind areas in the searching can lead the signal loss increasing remarkably once the the receiving UAS locates out of the steering ranges. Regarding the constraints, we optimize the searching space for OAODV and reduce the overhead of swarm UAS. There are multiple error resources derived from UAS mobility and networking fluctuations which can cause the optimal next hops dynamic and hard to decide. The fluctuation derived from the UAS networking can cause much energy consumption to optimize the solution, especially, the ambiguous selection is too exact. In this situation, our beamforming generation has a divergence angle which can enlarge the searching space and cover the fluctuation of the UAS networking. Apart from the natural divergence angles, our proposed approach can adjust the searching angles to extend the optimal selections and mitigate fluctuations effect. The next hops can be optimized based on the optimal selections extending in the fluctuated situations of UAS networking. The proposed OAODV is different from the conventional AODV which is suitable for the 5G cellular networking on the swarm UAS networking on a large scale. The difference between the scenarios is that the AODV can be deployed in a group and the members of the group can not exceed over 100. The OAODV aims to improve the swarm UAS networking to an amount that is over thousands. The massive implementations need much more efficiency, reliability, flexibility, and elasticity for the cooperation between different swarm UAS networking which is essential to the deployment of the cyber physical system in the future on the aerial areas.

The rest of the paper is organized as the following. Sec. II presents the related work for swarm UAS networking routing specifically. Sec. III presents the proposed system model and methodology of swarm UAS networking routing algorithms. Sec. IV provides the evaluation of the proposed algorithms. Sec. V concludes the results.

2 Related Work

Currently, there are many routing algorithms proposed for UAS networking. However, the majority of researches focuses on the UAS fleet which is smaller than swarm UAS in scale.

The distributed routing algorithms for UAS networking are mainly based on AODV [?], [?]. The authors compared AODV and OLSR in Flying Ad hoc Networks (FANETs) with the simulator of NS-2 [?]. The evaluation shows that OLSR is not suitable for highly-dynamic and low-density networking. In the research of [?], the evaluation shows that the time consumption of AODV on the initial path discovery stage is overwhelmed. And the authors, in [?], concluded the path discovery stage on the AODV can decrease the stability of FANETs. To mitigate this problem, an optimization is proposed to implement Dijkstra to extend the transmitting buffer. The results show that the optimization can reduce the latency between end-to-end communication [?].

In terms of the centralized routing algorithms, the main weakness of OLSR is overhead for topology maintenance in real-time. Based on the weakness, many researchers made a relative modification on OLSR to satisfy the requirement of communication. With constraints of the related speed between nodes, the authors in [?] proposed a predictive OLSR (P-OLSR) which predicts the transmission load and adjusts transmission count in real-time. Their evaluation shows that the P-OLSR outperforms OLSR and BABEL. Apart from the speed, the authors, in [?], proposed a mobility and load aware OLSR (ML-OLSR) for FANETs. Compared with OLSR, the simulations show that ML-OLSR can achieve lower end-to-end delay and high PDR. Similar research in [?], a multidimensional perception, and energy awareness OLSR (MPEAOLSR) is proposed. The MPEAOLSR can improve PDR, reduces packet loss rate, and end-to-end delay regarding node link time, link layer congestion, and node residual energy.

Flexibility is a distinctive advantage of swarm UAS, but also a great disadvantage of swarm UAS. The swarm UAS has more freedom to complete missions which also poses an immense challenge to swarm UAS networking. Due to the dynamic topology of UAS networking, the authors optimized the search space for a cube-based space region partition (CSRP) [?]. Their evaluations show that this partition could improve the performance of the average delay, packet delivery, and delay jitter. The main drawback is that it sacrifices the flexibility of swarm UAS. CSRP guarantees efficiency and low latency underneath the stability of networking. In [?], the authors acquire geographic information to enhance routing efficiency which collects localization of its peers and executes routing path in direction greedily. Their simulation shows that directional delivery can improve the performance of packet delivery ratio, average delay, and routing overhead. The combination of Greedy Perimeter Stateless Routing (GPSR) and AODV is proposed in [?] and optimized with Particle Swarm Optimization (PSO). This combination could improve PDR on the greedy routing stage and the flooding path-discovery stage.

The 5G NR cellular networking is impending to assist the evolution of swarm UAS networking. The compact and the affordable nodeB devices can be implemented into the mobile devices to extend the scale of 5G NR from the ground to the aerial [?]. The current research of 5G NR on routing mainly focus on the optimization of multiple resources allocation [?], and multiple combined problem resolving [?] of new characteristics of 5G NR and the conventional issues [?]. To improve the data rate with the enhancement of beam alignment, Signal-to-Noise Ratio (SNR) and Reference Signal Received Quality (RSRQ) are implemented to enhance the detection of beam alignment of mmWave 5G which can improve the capacity of each beam connection. With the combined prediction of target localization and mobility, the link-weight based routing can achieve an optimal route to transmit packets with Huffman coding for security [?]. With the optimization of channel quality and resource block allocation, the base stations can achieve the maximization of the cellular spectrum with multiple paths for routing [?]. The advantage of the optimization can provide Device-to-Device (D2D) communication when a small set of base stations are invalid [?]. As the most critical issue of 5G NR cellular networking in all fields, joint optimization of Virtual Networking Function (VNF) placement and multicast traffic routing has serious effects on the quality and the stability of links generated between nodes in the 5G NR networking [?]. A Mixed Integer Linear Programming (MILP) model can formulate the joint optimization of the multicast traffic routing and VNF placement with the minimum provisioning cost on VNF and links. Since the MILP is an NP-hard problem, the combination of single path routing and multipath routing can enhance the efficiency and the accuracy of problem resolving remarkably [?]. Similar to [?], an Integer Linear Programming (ILP) model [?] can formulate the problem of the joint multicast routing and OFDM resource allocation problem in D2D networking with consideration of limit spectrum reusing half-duplex operation, and contiguity in the resource block allocations. A two-stage optimization performs pre-admittance filtering to detect the states of networking and extends the reduced ILP model with the branch-and-cut method. With enabling Network Slice (NS) selection and routing of traffic through an NS, a framework for enabling negotiation, selection, and assignment of NSs can request applications to improve the Quality of Service (QoS) with static, dynamic, and hybrid routing in 5G networking [?]. At the same time, a fast request routing distributes traffic demands among source nodes intelligently and routes flow through intermediate nodes strategically. The joint optimization mainly focuses on source direction and flow routing in mobile networking with built-in content sources. The evaluation shows the maximum link utilization can extend significantly [?].

With the high capacity of bandwidth in 5G NR cellular networking, the minor errors on links can be amplified to degrade the performance of the communication between heterogeneous networking and devices [?]. The links quality of 5G NR cellular networking is critical to elevate the stability and the security of applications in the upper layers. The dynamic of swarm UAS cause the 5G NR enabled swarm UAS networking is more dependent on the quality of the links generated between heterogeneous networking including the aerial networking and the ground networking. To improve the fusion convergence rate of heterogeneous networking, Wireless Sensor Networking (WSN) and Mobile Ad-hoc Networks (MANET) are combined to improve the routing efficiency when disasters occur. The combined 2-layer routing can generate paths via WSN or MANET according to the types of packets in the delivery and the states of emergency [?]. The dynamic environment requires the stability of link quality. A routing and resource allocation (RRA) scheme based on self-organizing feature maps (SOM) can reorder the link set generated in RRA processing to achieve the optimal quality of service in the multi-core networks underneath beyond 5G networking [?]. Assisted with Ultra Dense Networking (UDN) [?], a particle swarm optimization can optimize the routing discovery and enhance the packet delivery rate, throughput, and energy saving to improve reliability and QoS for UDN in routing.

Apart from the reliability, the delay between end-to-end devices is also essential in the 5G NR cellular networking, especially in the packets delivery of swarm UAS networking. An anchorless routing is enhanced with Locator/ ID Separation Protocol (LISP). The control plane can achieve the optimal delay and provide services for user plane nodes [?]. Fueled by machine learning, Q-learning optimized the selection of nodes and generated the shortest paths for the maximization of throughput with avoidance of congested network nodes [?]. A deep reinforcement learning based autonomous synchronous signal routing algorithm leverage a Deep Neural Network (DNN) to learn the policy of the minimum link asymmetry. With the optimal result, the time synchronization can assist the remote controller to maintain the balance between the synchronous services request and network resources allocation with reduction of end-to-end latency [?].

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Fig. 1. Packets Delivery inside Swarm UAS

The impending trend of 5G NR cellular networking on every device stimulates the evolution of swarm UAS networking from many aspects [?]. However, there are still many issues waiting for researchers to explore and solve. The reliability, elasticity, and flexibility of swarm UAS networking require deep research stemming from 5G NR cellular networking [?]. The 5G NR based swarm UAS networking can extend the scale and the flexibility of 5G cellular networking on a large scale and smartly.

3 Enhanced AODV for Swarm UAS Networking

Different from the conventional UAS fleet, in this paper, swarm UAS is equipped with 5G NR cellular networking devices. Each UAS in the swarm can deliver packets and broadcast information via beamforming with desired receivers and senders. Due to the dynamic topology of swarm UAS, FANET is an optimized architecture for swarm UAS networking. FANET is an Ad-hoc based networking framework that allows UAS to join and leave freely. In FANET, UAS can utilize multi-hop to deliver packets and broadcast information (depicted as Fig. ??). Most importantly, FANET is decentralized which can enable networking to manage on a large scale. Concurrently, AODV is a reactive and decentralized routing algorithm that is suitable to implement on a large scale. The overhead of AODV is much lower than the centralized routing algorithms.

Based on the advantages of FANET and AODV, in this paper, we propose a novel routing algorithm, OAODV, which is swarm-oriented, AODV-based, and decentralized. With the optimized searching space, OAODV can reduce overhead. Thereafter, we leverage ACO to optimize OAODV to enhance routing generation which could be more smart and robust. The two problems in this part are proposed and resolved: (1) ADS-B Enabled OAODV; (2) Pheromones Assisted Routing Optimization.

3.1 ADS-B Enabled OAODV

The conventional UAS is equipped with Omni-directional connection devices that do not support direction pointing. The main method of the Omni-directional connection is based on broadcast with encoded packets. The drawbacks of the Omni-directional connection can not avoid information leakage and unnecessary energy consumption. With beamforming of 5G NR cellular networking, swarm UAS can deliver packets and receive information with desired directions [?]. With purposed directional pointing, beamforming can reduce much the redundant of communication resources.

Enhance with beamforming of 5G NR, in OAODV, we leverage ADS-B to broadcast positions and mobility of swarm UAS [?]. The source of UAS can get an approximate position of the destination, and deliver packets to the adjacent UAS which flies in the direction of destination (depicted as Fig. ??). Thereafter, the selected UAS, in adjacent, take the responsibility as relay UAS, and handover the packets to the destination. In the path discovery stage, the relay UAS steer beams close to the direction to the destination and avoid the path discovery in the undesired directions. With the geographic information shared via ADS-B, the relay UAS can calculate an approximated search space for the next hop selections in their delivery ranges. As depicted as Fig. ??, our proposed algorithm can discover multiple paths for routing which is more robust to the topology variation. Due to the prevention of loop generation, in the path discovery stage, we insert a label generated with the first hop to mark the RREQ of path discovery. With the marked RREQ, the relay UAS in the swarm drops the RREQs with recording labels. Based on the redundant of routing, the source can adjust the delivery routing to satisfy the transmission requirement regarding the existence of invalid routings caused by networking topology fluctuation.

OAODV aims to reduce the latency and the overhead of path discovery. In Fig. ??, the UAS in red circle is source (denoted as U_s) and its position is denoted as $P_s = (x_s,\ y_s,\ z_s)$, where x_s is the latitude of U_s position, y_s is the longitude of U_s position, and z_s is the altitude of U_s position. The UAS in green circle is destination (denoted as U_d) and its position is denoted as $P_d = (x_d,\ y_d,\ z_d)$, where x_d is the latitude of U_d position, y_d is the longitude of U_d position, and z_d is the altitude of U_d position. Based on the position of destination, the source derives the next-hop selection from the vector:

$$\overrightarrow{V_{(s,\ d)}} = (x_d - x_s,\ y_d - y_s,\ z_d - z_s) \tag{1}$$

and the angle (denoted as θ) which is the search range for next hop. Each UAS (denoted as $U_n,\ n = 0, 1, 2, 3, ..., N$) gets the set of next hops H:

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Fig. 2. Path Discovery in Direction of Destination

$$H = \{h\ |\overrightarrow{V_{(s,\ d)}},\ \theta\},\ h\ is\ next\ hop. \tag{2}$$

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Fig. 3. Path Discovery of OAODV

Each position of UAS is denoted as $P_n = (x_n,\ y_n,\ z_n)$. The vector between UAS is denoted as $\overrightarrow{V_{(n,\ n+1)}},\ n = 0, 1, ..., N$.

$$\overrightarrow{V_{(n,\ n+1)}} = (x_{n+1} - x_n,\ y_{n+1} - y_n,\ z_{n+1} - z_n) \tag{3}$$

We have

$$\overrightarrow{V_{(s,\ d)}} = \overrightarrow{V_{(s,\ 0)}} + \overrightarrow{V_{(N,\ d)}} + \sum_{n=0}^{N} \overrightarrow{V_{(n,\ n+1)}} \tag{4}$$

As depicted in equation (??), the whole routing $\overrightarrow{V_{(s,\ d)}}$ obtains the first hops $\overrightarrow{V_{(s,\ 0)}}$, the last hop $\overrightarrow{V_{(N,\ d)}}$, and the relay hops $\sum_{n=0}^{N} \overrightarrow{V_{(n,\ n+1)}}$. With $\overrightarrow{V_{(s,\ 0)}}$, the routing can be marked with distinction.

As depicted in Fig. **??**, U_s obtains the location of destination approximately via ADS-B and calculate the approximated searching direction $\overrightarrow{V_{(s,\ d)}}$. With the approximated searching direction, U_s obtains the searching space ϕ for the first searching $\overrightarrow{V_{(s,\ 0)}}$. The relay UAS, in the space ϕ, are selected as the next hops. At the first searching, each hop is identified with the insertion of $\overrightarrow{V_{(s,\ 0)}}$ into RREQ. Here, '0' means the first relay UAS. The first relay UAS forwards the RREQ to the following relay UAS. The following relay UAS receives the RREQ, and checks whether its stack exists the same record of $\overrightarrow{V_{(s,\ 0)}}$. The following relay UAS drops the RREQ which has been recorded in its stack. After each successful forwarding, the relay UAS will record the RREQ in its stack.

For the next hops searching, the following relay UAS follow the same searching space ϕ. Here, the ϕ is determined by the location of the current relay UAS, U_n, and the destination, U_s. With ADS-B, the current U_n can get the vector to destination, $\overrightarrow{V_{(n,\ d)}} = (x_d - x_n,\ y_d - y_n,\ z_d - z_n)$. With the velocity of the current relay UAS, $\overrightarrow{V_{n_v}} = (v_x,\ v_y,\ v_z)$ and $\overrightarrow{V_{(n,\ d)}}$, we can have $\nabla\overrightarrow{V_{(n,\ d)}}$ depicted as equation (**??**) and (**??**).

$$\nabla\overrightarrow{V_{(n,\ d)}} = \frac{\partial\overrightarrow{V_{(n,\ d)}}}{\partial\overrightarrow{V_{n_v}}} \tag{5}$$

$$\frac{\partial\overrightarrow{V_{(n,\ d)}}}{\partial\overrightarrow{V_{n_v}}} = \begin{bmatrix} \frac{x_d-x_n}{v_x} & \frac{x_d-x_n}{v_x} & \frac{x_d-x_n}{v_x} \\ \frac{y_d-y_n}{v_y} & \frac{y_d-y_n}{v_y} & \frac{y_d-y_n}{v_y} \\ \frac{z_d-z_n}{v_z} & \frac{z_d-z_n}{v_z} & \frac{z_d-z_n}{v_z} \end{bmatrix} \tag{6}$$

Based on the $\nabla\overrightarrow{V_{(n,\ d)}}$, we can have the center of searching space ϕ based on $\overrightarrow{V_{n_v}}$:

$$\phi_{center} = tran^{-1}(\nabla\overrightarrow{V_{(n,\ d)}}) \tag{7}$$

The ϕ_{center} is the angle between center of the searching space and the velocity of UAS. The next step is to determine the bound of the searching space. The steering range of beamforming is denoted as α, for communication. In different antenna arrays, α is variable. For convenience, we assume $\alpha = 180^\circ$ in this paper, and the center of beamforming is the same with the velocity, $\overrightarrow{V_{n_v}}$. To satisfy the requirement of routing path discovery, we propose a policy for rending the searching space θ. As Fig. **??** depicted, the red line denotes the vector of $\overrightarrow{V_{n_v}}$, the green line denotes $\overrightarrow{V_{(n,\ d)}}$. Searching space is depicted as θ, and the range of beam steering is depicted as α. Based on the calculation of ϕ_{center}, the θ is defined as follows:

$$\theta = \begin{cases} 2(\frac{\alpha}{2} - \phi_{center}),\ \phi < \frac{\alpha}{2} \\ \frac{\alpha}{2},\ \phi \geqslant \frac{\alpha}{2} \\ \alpha,\ \phi = 0 \end{cases} \tag{8}$$

With the determination of searching space, we can derive the bound from searching space ϕ which includes $\phi_{up},\ \phi_{bottom},\ \phi_{left}\ and\ \phi_{right}$, and obtain the slopes of bound, $K_{up},\ K_{bottom},\ K_{left},\ K_{right}$. With locations of adjacent UAS, the UAS, falling in the bound, are selected as the next hop set H_n. After receiving the RREQ, the destination responds a request reply (RREP) to the source and confirms the routing to the source. Destination follows the routing gathered by RREQ and backhaul RREP to the source.

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Fig. 4. Searching Space Definition

For the relay UAS, the pseudocode of next-hop selection is depicted as Algorithm **??**.

Generally, Greed Perimeter Stateless Routing (GPSR) has some similarities with our proposed OAODV routing algorithms which both obtain geographical information for the routing discovery. The following is the difference between GPSR and OAODV.

The GPSR will update the geographic information timely to its peers which will cost much energy and spectrum efficiency and is hard to deploy on a large scale for the swarm UAS networking. Geographical information is critical to the GPSR in the path discovery which needs frequent updating from peers and shares the same channels with regular communication. The consumption for scheduling for the packet delivery needs additional overhead of system for each UAS in the swarm UAS networking that is not efficient and cost much more queuing delay for the delivery.

Different from GPSR, the OAODV just update the geographic information when new path discovery needs which can save much energy consumption on the new path discovery. Concurrently, we adopt ADS-B as the geographic information supply which does not need to share an additional spectrum for the geographical information exchange. And ADS-B can have long distance transmission and low energy consumption for the management. The OAODV does not need central management for the routing which enables the OAODV can be implemented in the swarm UAS networking distributively and on a large scale ubiquitously. The OAODV can select the next hops with the destination directions that can have advantages of the optimal routing generation and over the greedy behaviors (GPSR). Compared with GPSR on the selection of the next hop, the

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Algorithm 1 Hops Selection of OAODV

procedure THE NEXT HOP SELECTION(H_n)
  $U_n \leftarrow RREQ;$
  $U_n \leftarrow source\_ID;$
  $U_n \leftarrow destination\_ID;$
  $U_n \leftarrow destination\_Position;$
  $U_n \leftarrow \overrightarrow{V_{(s,\ 0)}};$
  if $\overrightarrow{V_{(s,\ 0)}}$ *has been recorded* **then**
    Drop the RREQ;
    Stop procedure;
  else
    $Index_{U_n} \leftarrow \overrightarrow{V_{(s,\ 0)}}$
  end if
  $\overrightarrow{V_{(n,\ d)}} \leftarrow (x_d - x_n,\ y_d - y_n,\ z_d - z_n);$
  $\phi_{center} \leftarrow tan^{-1}(\nabla \overrightarrow{V_{(n,\ d)}});$
  $\phi_{left} \leftarrow \phi_{center} + 0.5 \times \theta;$
  $\phi_{right} \leftarrow \phi_{center} - 0.5 \times \theta;$
  $\phi_{up} \leftarrow \phi_{center} + 0.5 \times \theta;$
  $\phi_{bottom} \leftarrow \phi_{center} - 0.5 \times \theta;$
  $K_{up} \leftarrow tan(\phi_{up});$
  $K_{bottom} \leftarrow tan(\phi_{bottom});$
  $K_{left} \leftarrow tan(\phi_{left});$
  $K_{right} \leftarrow tan(\phi_{right});$
  while $Y_{n+1} < K_{left} \times X_{n+1}$ *and* $Y_{n+1} > K_{right} \times X_{n+1}$ *and* $Z_{n+1} < K_{up} \times X_{n+1}$ *and* $Z_{n+1} > K_{bottom} \times X_{n+1}$ **do**
    $H_n \leftarrow Select\ UAS;$
  end while
end procedure

OAODV is more purposeful to obtain the hops directing to destinations.

3.2 Pheromones Assisted Routing Optimization

In the above, we proposed OAODV to improve the capacity of networking routing for swarm UAS. Based on OAODV, we can obtain multiple routings for packet delivery, and some of them are redundant for the bandwidth requirement. The following problem is how to arrange multiple routings for packet delivery. In the communication, each routing is denoted as R_n, $n = 1,\ 2,\ 3,\ \ldots,\ S$. The requirement of bandwidth is denoted as BW, and the latency between end to end devices is denoted as L_{e2e}. Based on the routing capacity, we can have a convex optimization as follows:

$$\begin{aligned} &\arg\min \sum_{0}^{S} R_n \\ \text{S. T.}\quad &\sum_{s}^{N} b_w \geqslant BW \\ &\sum_{s}^{d} d_n + \sum_{n}^{H} p_{(i,\ j)} \leqslant L_{e2e} \end{aligned} \tag{9}$$

Where, R_n includes U_S, U_d, and relay hops H. bw represents the bandwidth of each routing. To the requirement of bandwidth, BW, we assume routings, derived from OAODV, are redundant. d_n is the delay for each UAS which mainly contains queuing delay. $p_{(i,\ j)}$ indicates the propagation in each hop. In this paper, we assume the latency of end-to-end for each routing mainly includes d_n and $p_{(i,\ j)}$.

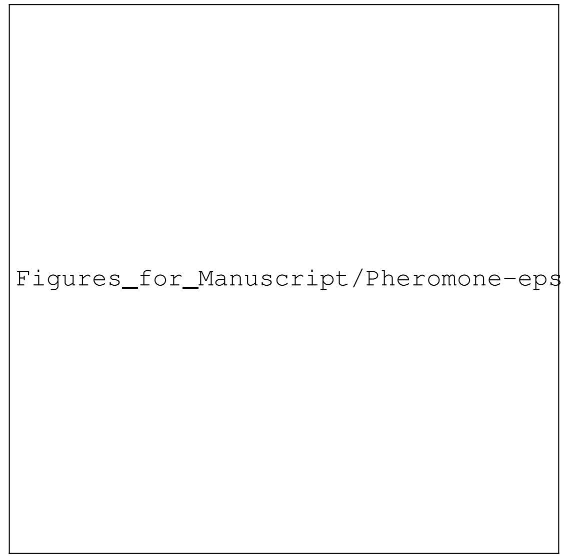

Fig. 5. Path Selection based on ACO

Further, we leverage ACO to improve networking routing for swarm UAS. The ACO is not the only choice for routing optimization. The ACO is a distributed algorithm that can be deployed in the scattered swarm UAS networking. The ACO leverage pheromone to mark the states of traffic that can be updated with packet delivery and path discovery simultaneously. In ACO, each agent can be assigned several behaviors which are simple and storage efficiency over the particle swarm optimization, fish swarm intelligence, and other swarm optimizations. However, the conventional ACO focuses on single path optimization which is not suitable for OAODV and can not meet the dynamic variation of topology. Based on $\overrightarrow{V_{(s,\ 0)}}$, each hop is marked with pheromone, and only the hops with high pheromone can be selected. To each routing marked with $\overrightarrow{V_{(s,\ 0)}}$, local optimization is completed with ACO, which means the global optimization for swarm UAS is achieved with maximum optimization of each routing.

In ACO, each agent uses the pheromone to mark the next hops. The agent selects the next stop which has higher pheromone. Each UAS stores the pheromones of the adjacent UAS, $Ph = \{Ph_n\},\ n = 0, 1, 2, ..., N$. In the set of H_n, the UAS selects the one with max pheromones $Max(Ph)$. Among the multiple paths, the UAS selects the highest Ph_n to keep the cumulative pheromones max (denoted as $Max(Ph) = Max\{\sum Ph_n |\ n \in H_n\},\ n = 0, 1, 2, ..., N$). Here, we utilize the response time τ_n as the stimulation of pheromone updating. τ_n includes d_n and $p(i, j)$. The probability of UAS selects the next hop, P_{Ph_n}:

$$P_{Ph_n} = \begin{cases} \frac{Ph_n \times (\frac{1}{\tau_n})}{\sum Ph_n \times \frac{1}{\tau_n}},\ (\tau_n < \infty) \\ 0,\ otherwise \end{cases} \tag{10}$$

The pheromone is updated based on each successful delivery.

$$Ph_n \leftarrow (1 - \alpha) \times Ph_n + \sum_{k=1}^{m} \triangle Ph_n \tag{11}$$

Here, $0 < \alpha < 1$ is the pheromone decay parameter, and $\triangle Ph_n$ is,

$$\triangle Ph_n = \begin{cases} \frac{1}{\tau_n}, if\ UAS\ n\ is\ selected \\ 0,\ otherwise \end{cases} \tag{12}$$

With the modified ACO, the optimization is not limited to the specific iterations. Each delivery can be considered as an optimization that is continuous and dynamic. The continuous updating of pheromone is derived from a delivery that can track the status of networking in real-time. The distribution of pheromone accumulation renders the networking status simultaneously. The updating distribution of pheromone enables the most efficient delivery distributively [?]. The decay parameter is critical to the performance of pheromones marking. The decay parameter decides the percentage of involvement of the history. Due to the dynamic of swarm UAS networking, the traffic of the routing is supposed to be variable to the variance of environment and mission assignments. If the traffic is under the updating of the high speed, the decay parameter will be set to smaller than 0.5, and the current states will affect the final decision more. Otherwise, the decay parameter is supposed to be set over 0.5, the sluggish scenarios are more dependent on the historical data to keep the whole decision steady. Due to our focus on the routing part in a tiny time slot, our intending is to choose the 0.5 as a balance between the history and the current states which is shown in the evaluation part.

In the scenario, we assume each UAS has an equal bandwidth, bw, for packet delivery. The objection of optimization can be converted into a selection. This selection is assigned to U_s. The U_s can adjust the paths selection which is subjected to L_{e2e} and BW. U_n take the delivery request of the packet. The decision of the next hop is selected with P_{Ph_n}. U_n calculates P_{Ph_n} and selects the one with high pheromone. After the delivery of packets, U_n count the backhaul packets for the updating of Ph_n. Once the τ_n changed, Ph_n will be updated with the affection of the previous Ph_n and the accumulation of $\sum_{k=1}^{m} \triangle Ph_n$. The specific processing of Algorithm **??** is as follows:

Algorithm 2 ACO Enabled OAODV

procedure THE LEAST HOP OPTIMIZATION ($\arg\min \sum H_n$)
  $U_s \leftarrow \{Rn\}$;
  $U_s \rightarrow \{\overrightarrow{V_{(s,\,0)}} \mid U_0\ is\ selected\}$
  if $\overrightarrow{V_{(s,\,0)}}$ **then**
    $P_{Ph_n} \leftarrow Ph_n$;
    $Deliver\ Packet$;
    $Check\ RREP$;
    if $T_{RREP}\ Changed$ **then**
      $Ph_n \leftarrow \frac{1}{\tau_n}$;
      $Update\ Ph_n$;
    end if
  end if
end procedure

4 EVALUATION

In this section, the results of the evaluation are conducted with Matlab 2019b and the networking configuration is referenced with the NS-3.29 simulator (waf 2.0.18). The whole routing generation processing obtains path initial stage (depicted as Fig **??**), path discovery processing stage (depicted as Fig **??**), and path discovery complement stage (depicted as Fig **??**). The routing path is generated after the path discovery complement. Based on the generated routing, we evaluated the performance of communication which aims at latency, overhead, and searching link generation with the comparison of OLSR and AODV algorithms. Pheromone assisted routing selection is depicted as the following figure: (Fig **??**, Fig **??**, Fig **??**). We can achieve multiple routings with Algorithm **??**, and then the pheromone assisted routing selection is implemented to optimize the routings for swarm UAS. The ACO performance is evaluated based on the OAODV multiple paths generation which focuses on average hops reduction and average throughput increment.

TABLE 1
parameters of swarm uas configuration

Mobility Model	ConstantVelcityMobilityModel
Swarm Distribution Space	100 m * 100 m * 5 m
Speed	10-15 m/s
Movement Direction	[1, 2, 3]
Transmission Rate	1 Mbps
Transmission Range	15 m
Beam Steering Range	0-180 °
Transmission Protocol	UDP
Latency Requirement	$\leq 110\ ms$
Bandwidth Requirement	$\geq 2\ Mbps$
Evaluation Runs	10000
Each Evaluation Time	20 s

4.1 Parameters of UAS in Swarm

The configuration of UAS in the swarm is depicted as the Table **??**. Based on the swarm UAS mobility, in this evaluation, we configured the mobility model, swarm distribution space, and movement direction ($\overrightarrow{V_{n_v}}$). The constant velocity of UAS for swarm UAS networking is that the swarm UAS needs to keep the formation of the whole swarm UAS networking which has minor differences between each other. In some aspects, the mobility model we take has the characteristics of variable velocity without significant variation. The great variation of speed on swarm UAS networking can cause the separation of the swarm UAS networking which is critical to the construction of UAS communication in the flight. Generally, each UAS has its noise for the speed control which has no big effect on the generation of the topology of swarm UAS networking that means the variable velocity does not make an effect on the integrity of swarm UAS networking. Therefore, the routing algorithms do not have different performance on the integrated topology of swarm UAS networking. In the swarm mobility model, each UAS keeps static with its neighbors which means that in the whole processing the distribution space is not variable for each evaluation. We simplify the waypoints of swarm UAS into the static distribution space which could enable us to observe the path discovery processing more distinctly. In swarm communication, each UAS has a limited transmission range, and the UAS can not deliver packets to the UAS which is out of the range of beam steering (depicted in Table **??** specifically). To explore the performance of pro-

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Fig. 6. Path Discovery Initial Stage

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Fig. 7. Path Discovery Processing Stage

posed algorithms, we executed 10000 runs of the evaluation for gathering enough data.

4.2 Evaluation of Searching Angles for OAODV

Due to the characteristics of beam steering, we explored the performance of OAODV with variable searching space which is mentioned as searching angle θ. In this evaluation, we assume the active range of beam steering is 180°. Based on the variable searching angle (θ), we explored the capacity

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Fig. 8. Path Discovery Complement Stage

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Fig. 9. OAODV Multiple Paths Discovery

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Fig. 10. OAODV Multiple Routings

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Fig. 11. OAODV Multiple Routings Pheromone

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Fig. 12. Angles Searching Performance

of overhead, latency, and link generation on average. Based on the effect of the amount of UAS, we chose the median amount, 100, to perform the evaluation. The average evaluation results are depicted in Fig **??**. The average overhead and the average latency show similar trends which keep steady as the searching angle rises from 10° to 60°, and increase rapidly as the searching angle expands from 70° to 100°. Thereafter, the average latency and the average overhead fluctuates in the range ($110^\circ \sim 180^\circ$). From our observation, the searching angle at the range, 10° to 60° can achieve better latency and overhead. However, the OAODV, in this range, obtains less throughput than the throughput generated in the range of $110^\circ \sim 180^\circ$. The average link generation shows a similar trend as the searching angles increase. Fig **??** shows, in the communication, the trade-off between latency, overhead, and throughput is significant.

4.3 Path Discovery Comparison

With the result of Fig. **??**, the trade-off between the lowest latency and the lowest overhead for UAS networking is challenging simultaneously. In this evaluation part, we choose 90° as the searching angle range regarding the balance of latency and overhead for UAS networking. The optimal searching angle is supposed to be variable according to the states of the UAS networking which can achieve the best balance between the latency and the overhead of the UAS networking in real-time. In this part, we just proposed a fixed parameter selection for the balance of the routing discovery with the purpose of optimization of whole connections constructions. To show the distinction of the OAODV, we illustrated the complement of AODV, OLSR, and OAODV in the following figures (Fig **??**, Fig **??** and Fig **??**).

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Fig **??** shows the path discovery of AODV in the swarm which contains 100 UAS. In the path discovery processing, the nodes will abort the packets which duplicated broadcast with the purposed of loop avoidance. Each UAS in the swarm is marked with a pink circle when it received the RREQ. From Fig **??**, we can observe that there are still some UAS not being received RREQ. This means that the overhead of the swarm system is not full. In the evaluation, we assume the overhead is occupied after the UAS received forwarding missions, and the overhead of UAS is equal when it is on the forwarding mission.

Fig **??** shows the path discovery of OLSR in the swarm which contains the same amount of UAS with Fig **??**. In the path discovery processing, the OLSR needs to get all the link states of the whole networking so that we can observe the searching link generation (depicted in blue line) are more than the AODV which means the overhead of OLSR is much higher than AODV. The high overhead of OLSR could get the reward of shorter routing which is marked in the red line.

Fig **??** shows the path discovery of OAODV with single routing finding in the same scenario with Fig **??** and Fig **??**. In this scenario, the UAS aborts the RREQ with the same broadcast ($\overrightarrow{V_{(s,\,d)}}$). In Fig **??**, we can observe that the overhead of OAODV is much less than AODV and OLSR. Concurrently, the AODV can achieve a shorter path as OLSR. Based on the results of Fig **??**, we made a trade-off between overhead, latency, and throughput, we set the searching angle for 90° to achieve better performance. Thereafter, the configuration is the same in the following evaluation.

Apart from the path discovery complement in Fig **??**, Fig **??**, Fig **??**, we also depicted the performance of different algorithms in variable amount of swarm UAS in the following figures: Fig **??**, Fig **??** and Fig **??**.

Fig **??** shows the average searching link generation for AODV, OLSR, and OAODV. The average link generation of OLSR shows exponential increment as the amount of UAS in the swarm. The increment shows that the overhead of the swarm UAS grows rapidly when the amount of swarm UAS extends. Generally, the AODV and the OAODV keep steady as the amount of swarm UAS grows. Slightly, the OAODV generates less searching links than AODV.

Fig **??** shows the average latency of the AODV, OLSR, and OAODV. In this evaluation, the latency obtains the propagation, queuing time for each routing. In Fig **??**, the AODV achieves the highest average latency as the amount of UAS increases. The OLSR keeps 60 ms of latency roughly with the increment of the amount of UAS in the swarm. Before the amount of UAS ended up 90, the OAODV shows an increasing trend of average latency and lower than OLSR. After the amount of UAS reached 110, the average latency of OAODV is becoming steady as the amount of UAS rise. Compared with AODV and OLSR, OAODV can reduce 47.73% and 11.55% of the average latency respectively.

Fig **??** shows the average overhead of AODV, OLSR, and OAODV. Due to the characteristics, the overhead of OLSR keeps 1.0000 as the amount of UAS expands. The average overhead of AODV fluctuates from 0.4226 to 0.7552 as the amount of UAS rise. The average of OADOV keeps growing as the amount of UAS rises from 10 to 110, and then fluctuates between 0.3402 and 0.4692 from 120 to 200.

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Fig. 13. AODV Path Discovery

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Fig. 14. OLSR Path Discovery

Generally, compared with AODV and OLSR, OAODV can reduce 35.07% and 68.93% of the overhead respectively.

4.4 ACO enabled OAODV

Based on the Algorithms **??** and constraints in Table **??**, we achieved Fig **??**. The $\overrightarrow{V_{(s,\,0)}}$ enables us to obtain multiple routings with different labels. Thereafter, we can gain more throughput for swarm UAS networking. Fig **??** shows the comparison of average hops between the OAODV and the

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Fig. 15. OAODV Path Discovery

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Fig. 16. Average Searching Link Generation

ACO enabled OAODV. The result shows that the ACO can reduce the redundant hops to achieve a shorter routing. Fig **??** depicts the average throughput of the comparison between OAODV and ACO enabled OAODV. The result shows the ACO can improve the throughput of swarm UAS networking efficiently as the amount of swarm UAS increases.

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Fig. 17. Average Latency Comparison

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Fig. 18. Average Overhead Comparison

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Fig. 19. Average Hops Generation

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Fig. 20. Average Throughput Comparison

5 Conclusion

In this paper, we proposed a novel algorithm, OAODV, which aims to improve the performance of swarm UAS networking that is limited by the constrained beamforming. With the adjustable searching space, our proposed approach can achieve better latency, overhead, and link generation than the conventional algorithms of AODV and OLSR. Compared with AODV and OLSR, our proposed approach can reduce 35.07% and 68.93% of the overhead respectively, and decrease 47.73% and 11.55% of the average latency. With the optimization of ACO, our proposed approach can obtain better throughput and fewer hops in the routing with the purposed of reduction of overhead. The proposed algorithms show a promising capacity to improve the performance of the swarm UAS networking. In the future, we will continue to explore the optimization for the balance between searching angles and throughput of the swarm UAS networking.

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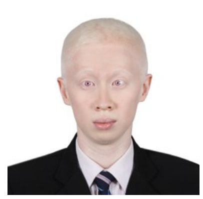

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