IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Transmitter-Selection aided Adaptive Consensus-Based Data Sharing for UAV Swarms

Yanqi Zhang[1], Bo Zhang[2], Xiaodong Yi[2], Jiankang Zhang[3,4]

[1]State Key Laboratory of High Performance Computing, School of Computer, National University of Defense Technology, Changsha, 410073, China
[2]Artificial Intelligence Research Center, National Innovation Institute of Defense Technology, Beijing, 100010, China
[3]School of Electronics and Computer Science, University of Southampton, Southampton SO17 1BJ, U.K.
[4]School of Information Engineering, Zhengzhou University, Zhengzhou, 450001, China

Corresponding author: Bo Zhang (e-mail: bo.zhang.airc@outlook.com).

This work is supported by the National Natural Science Foundation of China (No.91648204, No.61601486, No.61571401), Research Programs of National University of Defense Technology (No.ZDYYJCYJ140601), and State Key Laboratory of High Performance Computing Project Fund (No.1502-02). Part of this work was presented in the 14-th International Conference on Collaborative Computing, and this work is devoted to an improved design of transmitter-selection aided consensus data sharing, a novel UAV swarm simulation platform design and implementation, along with new experimental results and insights.

ABSTRACT The unmanned aerial vehicle (UAV) swarm systems rely on wireless communications for data sharing and coordination. Recently, both the lazy and eager consensus-based algorithms were proposed to enable swarm-wide data sharing. However, our analysis and experiments show that the performance of both algorithms may degrade drastically in dynamic and heterogeneous network environments. The reason is attributed to the fixed transmitter selection strategies adopted in the algorithms. Therefore, in this paper, we propose a novel adaptive consensus data sharing algorithm by adopting single best transmitter selection to strike a beneficial tradeoff between convergence rate and payload cost. Then, we propose and implement a UAV swarm simulation platform to facilitate simulations in dynamic and heterogeneous environment. Numerical results reveal that the proposed adaptive consensus-based data sharing algorithm performs well across different network scenarios in terms of convergence rate and payload cost.

INDEX TERMS Multi-UAV, Consensus data sharing, Heterogeneous network environments

I. INTRODUCTION

The unmanned aerial vehicle (UAV) is emerging as a disruptive technology in many areas of science, technology, and society, including surveillance, transportation and combat systems [1]. As a UAV needs to interact with geographic and communication environments, a considerable amount of research focuses on robot perception, recognition, motion/path planning and control. Compared with a single UAV, a swarm of UAVs may facilitate distributed perception and task execution, offering higher robustness, fault tolerance and inherent parallelism [2]. Therefore, UAV swarms can be applied to a wider range of mission areas. The U.S. Strategic Capability Office, Naval Research Office and DARPA have proposed and accelerated the development of high-performance UAV swarm [3]. Faced with the complex tasks that are difficult to accomplish by a single UAV, a UAV swarm may greatly improve the efficiency of task execution through collaboration. When the environment changes or a local system failure occurs, the mission may still be accomplished through distributed control, such as multi-target tracking [4] and RF-source localization [5].

The benefits of UAV swarms rely on distributed sensor information fusion and distributed consistency control, which requires data sharing among UAVs to achieve sensing and control information consensus [6], [7]. Wireless communication is the primal way of data sharing in UAV swarms. However, the realistic wireless communication environments experiencing path-loss, fading, shadowing and interference may significantly affect the achievable throughput for payload transmission for UAV swarm coordination [8]. Against this background, this paper is devoted to spectrum-efficient, reliable and timely data sharing algorithm design for UAV swarms.

Consensus-based data sharing algorithms have been considered for sharing swarm-wide situational awareness data in many multi-agent coordination problems [9], [10]. The authors of [11] proposed the lazy and the eager algorithms in UAV swarms, where the convergence rate and payload cost are evaluated and compared in static networks and the simulations assumed homogeneous network topologies. Therefore, in this paper we first evaluate and analyze the performance of the lazy and eager algorithms in time-varying networks and considers heterogenous network topologies. According to the simulation results, neither the lazy nor eager algorithms may perform well in dynamic network scenarios. Therefore, it is not practical to adopt them on UAV swarms in the presence of realistic environments.

Our analysis shows that the inferior performance of the lazy and the eager algorithms in certain network scenarios attributes to their fixed transmitter selection strategies. Therefore, we propose an adaptive algorithm that adaptively switches transmitter-selection strategies according to the instantaneous communication channel quality, and adopt the single transmitter selection scheme to improve the spectrum efficiency. Also, in order to compare and validate the performance of different data-sharing algorithms, we propose and implement a simulation platform for UAV swarms. Through experimental results, it is shown that the proposed adaptive consensus-based data sharing algorithm performs well across different network conditions.

The remainder of the paper is organized as follows. The network model for data-sharing in UAV swarms is given in Section 2. Section 3 provides careful analysis of both the lazy and the eager data-sharing algorithms, then describe the proposed adaptive data-sharing algorithm in detail. In order to support UAV swarm simulations in dynamic and heterogenous network scenarios, Section 4 is devoted to the simulation platform design and implementation, which facilitates the comparative performance analysis for different data-sharing algorithms in Section 5. Finally, conclusions are drawn in Section 6.

II. NETWORK MODEL AND ASSUMPTIONS

The information exchange network in the UAV swarm of m UAVs is modeled by a time-varying directed graph of m vertexes. A time-varying network model is adopted, where the communication quality changes due to the UAV motion and topology variations. Specifically, a weighted time-varying adjacent matrix $A(t)=[a_{ii}(t)]\in R^{m\times m}$ is adopted, where $a_{ii}(t)$ denotes the transmission success probability of the wireless channel spanning from UAV i to UAV j at time t [12][13]. In order to simplify the network model and performance evaluation, it is assumed that the UAV swarm is time-synchronous and the communication time slot is discretized, namely, the adjacent matrix changes at discrete time-step and the information exchanging process is decomposed into multiple communication rounds. During each communication round, the message exchange between UAVs adopts UDP/IP broadcasts without ACK/NACK and retransmissions.

In order to measure and evaluate the communication quality of multi-UAVs during motion and lay the foundation for multi-UAV communication simulation, we first analyze and model the wireless channel, and then calculate the inter-UAV packet error rate. In the air-to-air channel, we may assume that the effects of fading and shadowing is negligible, then the channel may be simplified to an additive white gaussian noise (AWGN) channel, and the instantaneous received signal-to-noise ratio (SNR) $\gamma_{i,i}$ is only affected by the path attenuation. The channel bandwidth is B (Hz), N_0 (W/Hz) represents the power spectral density of the AWGN, and β is the path attenuation index of the channel. The transmit power of the sender UAV i is denoted by P_i, and the received SNR of the receiver UAV j can be expressed as:

$$\gamma_{i,j}=\frac{P_i}{{d_{i,j}}^{\beta}N_0B} \tag{1}$$

where x_i and x_i denotes the location of UAV i and j, while $d_{i,i}=\|x_i-x_i\|$ represents the Euclidean distance between UAV i and UAV j. Please note that the AWGN channel model will not affect the data-sharing algorithm design, and for ground vehicles and UAVs in complex terrains, shadowing and fading may also be included in the model to better capture the instantaneous received SNR.

According to [14], the instantaneous point-to-point packet error rate between the transmitting UAV and the receiving UAV can be expressed as a function of $\gamma_{i,i}$:

$$p_n(\gamma_{i,j})\approx\begin{cases}1, & 0<\gamma_{i,j}<\gamma_{pn}\\ a_n\exp(-g_n\gamma_{i,j}) & \gamma_{i,j}>\gamma_{pn}\end{cases} \tag{2}$$

where n is the index of the transmission mode, indicating different modulation and channel coding modes. γ_{pn}, a_n, g_n is a constant associated with the transport mode.

III. CONSENSUS DATA SHARING ALGORITHM DESIGN

The lazy and eager algorithms were proposed in [11] and their performance evaluated in static and homogenous lossy environments. In this section, the applicability of both algorithms in dynamic and heterogenous lossy environment are implemented, which reflects their performance in more realistic UAV-swarm scenarios .

Specifically, we analyze and compare the performance of the consensus data sharing algorithms in terms of convergence rate and payload cost. By carefully analyzing the experimental results and the data sharing mechanism, it is shown that the data sharing process may be transformed into a sequence of transmitter selection, and the lazy and eager algorithms use different transmitter selection strategies but both strategies are static. Therefore, their performance may be well in a certain scenario, while may also degrade drastically in dynamic scenarios. Against this finding, we insert adaptive transmitter selection module into the consensus data sharing algorithm and propose the adaptive algorithm, which is capable of accommodate dynamic communication environments and achieves a beneficial tradeoff between the convergence rate and payload.

A. LAZY AND EAGER CONSENSUS DATA SHARING ALGORITHMS

In a UAV swarm, each UAV may generate its own data, e.g. environment sensing or task information, etc. Once the data is requested by other UAVs, both the lazy and eager algorithms drive each UAV to request data it does not own, meanwhile respond and broadcast its own data, until each UAV eventually obtains data from all other UAVs. In this way, reliable dissemination of the data in the swarm is guaranteed.

In order to implement the above mechanisms and allow cross-algorithm comparisons, we followed the variable naming in [11] and defined two initialization variables *swarm* and *data_avail*. The variable *swarm* represents the set of UAVs from which the data is required. The variable *data_avail* denotes the set of UAVs for which the data are obtained. At initialization, the swarm set contains all swarm UAVs, while the data avail set contains only the executing UAV owing its own generated data. In each communication round, a UAV may broadcast request messages and data messages according to its status. A request message contains all UAV IDs for which the data are required, where a data message contains a set of ID/data tuples.

The specific description of the lazy and eager algorithms is shown in Alg. 1 and Alg. 2 [11]. It is noted that the major difference between these algorithms is the UAV's reactions strategies towards the request messages. In the lazy algorithm, an UAV responses with a data message only containing its own data. In the eager algorithm, an UAV responses a data message containing all the requested data it has, namely, not only its own generated data but also data regenerated in previous communication rounds during the information exchange process.

ALGORITHM 1
THE LAZY CONSENSUS DATA SHARING ALGORITHM

```
swarm ← swarm_UAV_ids
data_avail ← {own_data}
repeat
  if ∃ UAV ∈ swarm ∧ UAV ∉ data_avail then
    new_data ← NET_RECV_DATA
    data_avail = data_avail ∪ new_data
    own_request ← swarm \ data_avail
    NET_SEND_REQUEST(own_request)
  end if
  requests ← NET_RECV_REQUESTS
  if own_data ∈ requests then
    data_to_send ← own_data
  else
    data to send ← ∅
  end if
  NET_SEND_DATA(data_to_send)
until terminated
```

ALGORITHM 2
THE EAGER CONSENSUS DATA SHARING ALGORITHM

```
swarm ← swarm_UAV_ids
data_avail ← {own_data}
repeat
  if ∃ UAV ∈ swarm ∧ UAV ∉ data_avail then
    new_data ← NET_RECV_DATA
    data_avail = data_avail ∪ new_data
    own_request ← swarm \ data_avail
    NET_SEND_REQUEST(own_request)
  end if
  requests ← NET_RECV_REQUESTS
  data_to_send ← requests ∩ data_avail
  NET_SEND_DATA(data_to_send)
until terminated
```

As shown in Figure 1, the data sharing process may be transformed into sequence of transmitter selection, while the lazy and eager algorithms adopt two different transmitter selection strategies. In Figure 1, the "decoding set" represents the set of UAVs owning the requested data, including the source UAV, and the decoded UAVs those have successfully regenerates the data from the source UAV. The destination UAV does not have the data from the source UAV, so it sends a request message.

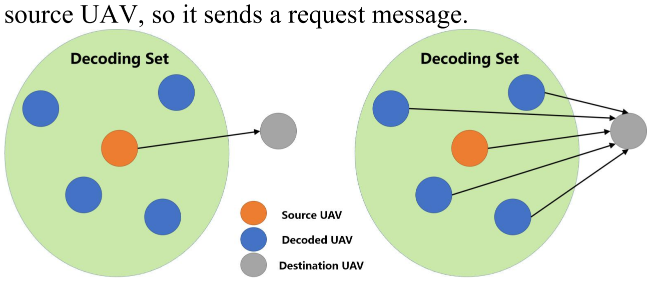
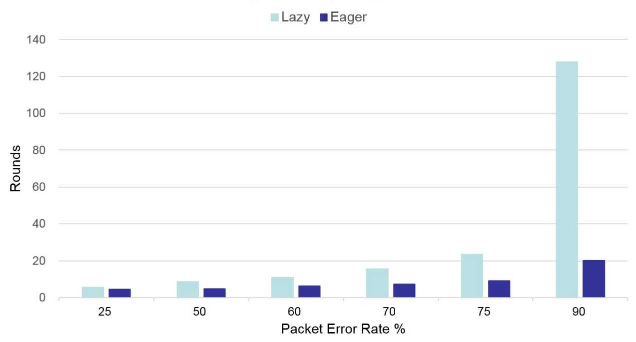


FIGURE 1. The transmitter selection strategies in lazy and eager consensus data sharing algorithms. The destination UAV request the data generated by the source UAV, while the decoded UAVs have successfully re-generates the data disseminated by the source UAV.

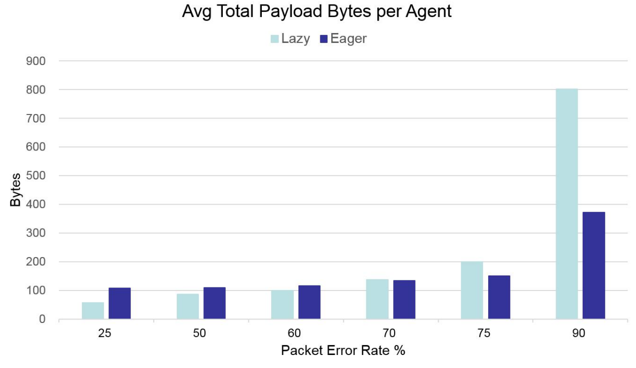
In the lazy algorithm, only the source UAV responds to the request message sent by the destination UAV and transmits data in a communication round. In contrast, in the eager algorithm, all UAVs in the "decoding set" forward data upon receiving the request message from the destination UAV.

With the aid of multi-channel diversity gain, the eager algorithm may achieve the optimal diversity gain of K , where K is the size of the decoding set. The diversity gain improves the transmission success probability, thus may accelerate the convergence of the data sharing process [15]. However, the diversity gain of K or reliability improvement is achieved at the cost of sending K message payloads per round, reducing the spectrum efficiency in the low packet loss scenarios. In contrast, the lazy algorithm introduces a low payload cost, at the cost of achieving a diversity order of 1, leading to a lower transmission reliability and slows down the convergence rate in high packet loss scenarios.

The extremes of both strategies limit their adaptability to different packet loss environments. Simulation results observed in static and homogeneous network scenarios also support this point. Both algorithms were tested in static network scenarios, where the homogeneous communication packet loss rates ranges from 25% to 90%, and the results are illustrated in Figure 2,. In low-loss communication environments (i.e., packet loss rate of 25%), the convergence rate of the eager algorithm is slightly faster than the lazy algorithm, but the total message payload bytes required by the eager algorithm is significantly higher. In contrast, in high-loss communication environments (i.e., packet loss rate of 75% and 90%), the eager algorithm outperforms the lazy algorithm, achieving both a faster convergence rate and a lower payload cost.



(a)



(b)

FIGURE 2. The (a) convergence rate and (b) payload cost of the lazy and eager algorithms in static and homogenous communication environments for different packet error rates.

Therefore, neither the lazy of eager algorithms may perform well in different packet loss situations. The reason is illustrated in Figure 1. On one hand, the multi-transmitter strategy in the eager algorithm may not reduce unnecessary payload in low packet loss case. On the other hand, the single-transmitter UAV aided strategy in the lazy algorithm relies only on the direct link between the source UAV and the destination UAV, and if the link quality is poor, the convergence rate may degrade drastically.

Furthermore, the performance of both lazy and eager algorithms may become worse if the packet loss rates are heterogenous and dynamic across the network. In order to adapt to the realistic communication environments, we design an adaptive consensus data sharing algorithm that makes a compromise between those two algorithms, using a transmitter selection scheme to select the appropriate responders.

B. ADAPTIVE CONSENSUS DATA SHARING ALGORITHM

In the area of cooperative communications, a series of relay selection schemes were proposed [15], and we choose single transmitter selection schemes for our adaptive algorithm, as it achieves a full diversity order at a low payload cost, which is illustrated in Figure 3. Specifically, the nearest neighbour selection scheme [16], [17] is adopted by selecting "the best transmitter" having the best channel quality towards the destination UAV, achieving a full diversity order and requires only one unit of payload. However, "the best transmitter" is dynamic for each transmit round, therefore demands an online mechanism for selecting and scheduling the UAVs in the decoding sets.

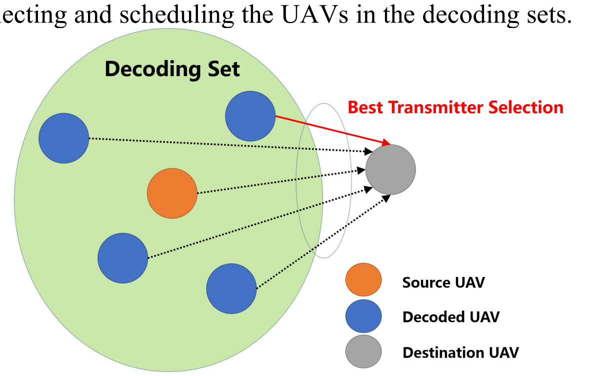


FIGURE 3. The transmitter selection strategies in the adaptive consensus data sharing algorithm.

A distributed timer technique is proposed for distributed transmitter selection motivated by [18]. Each UAV listens for request packets broadcasted by the destination UAV and competes for transmission. Upon receiving the request packet, each UAV resolves the request information in the pilot. If the UAV has the request data, it joins the decoding set. Meanwhile, the UAV uses the request packet to estimate the channel quality towards the destination UAV. and sets a timer having a count-down duration inversely proportional to the channel gain. Therefore, the timer of the "best" UAV expires first and it broadcasts a flag packet to inform other UAVs to stop their timers. Afterwards, the "best" UAV broadcasts the payload.

The adaptive consensus algorithm introduces a broadcast flag packet to assert winning the competition. The additional payload is *1*-bit in a IP-based networks or *log2(N)* bit in networks without UAV network identifiers, where N is the number of UAVs in the network. However, in the ad-hoc style network adopted in this paper, each UAV has an IP, so a *1*-bit indicator is sufficient. Furthermore, the CSMA/CA based medium access control (MAC) layer protocol may embed the indicator bit in the Request-to-Send (RTS) packet, so that the spectrum penalty is negligible.

The adaptive consensus data sharing algorithm is given in Alg. 3, which starts with the same initialization as in the lazy or eager algorithms. At the beginning of each communication round, if the UAV has not yet received the data from all other UAVs, the *data_avail* set is updated and a request packet is broadcasted, indicating the missing tuples in the *data_avail* set. In the middle of each communication round, all received request messages will be processed.

Upon receiving a request packet from the destination UAV, whether it is initially available to the executing UAV or obtained through information exchange, it competes for the "best" transmitter by starting the timer by setting a count-down duration inversely proportional to the channel gain towards the destination UAV. Then it waits for timers to expires or to be interrupted by flag packets from other UAVs. If no flag packet is received until the timer expires, it broadcasts a flag packet and declares itself as the best transmitter. The detail implementation of distributed transmitter selection process is shown in line 12 to 25 of Alg. 3, where a single UAV is selected to respond to a request packet in each communication round.

ALGORITHM 3
THE ADAPTIVE CONSENSUS DATA SHARING ALGORITHM

```
1: swarm ← swarm_UAV_ids
2: data_avail ← {own_data}
3: repeat
4:    if ∃ UAV ∈ swarm ∧ UAV ∉ data_avail then
5:       new_data ← NET_RECV_DATA
6:       data_avail = data_avail ∪ new_data
7:       own_request ← swarm \ data_avail
8:       NET_SEND_REQUEST(own_request)
9:    end if
10:   requests ← NET_RECV_REQUESTS
11:   data_to_choose ← requests ∩ data_avail
12:   for data ∈ data_to_choose do
13:      start a timer
14:   end for
15:   data_to_send ← ∅
16:   repeat
17:      flag_packets ← NET_RECV_FLAG_PACKET
18:      if ∃ timer ∈ Timers expires and receives no flag_packet
         then
19:         NET_SEND_FLAG_PACKET
20:         data_to_send= data_to_send ∪ data
21:      end if
22:      if ∃ timer ∈ Timers not expires and receives flag_packet
         then
23:         stop the timer
24:      end if
25:   until ∀ timer ∈ Timers expires or stopped
26:   NET_SEND_DATA(data_to_send)
27: until terminated
```

IV. SIMULATION PLATFORM DESIGN AND IMPLEMENTATION

In order to simulate data sharing for UAV swarms in realistic communication environments, we design a simulation platform for UAV swarms, which may simulate the UAV's interactions in both the geographic and communication environments. The architecture of the simulation platform is illustrated in Figure 4.

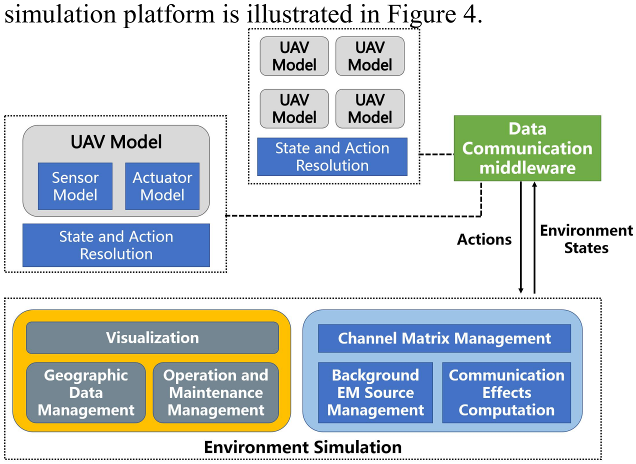


FIGURE 4. The architecture of the UAV swarm simulation platforms

The simulation platform is decomposed into two loosely coupled systems, namely, the environment simulation system and the UAV simulation system. The two systems exchange environment state and UAV action messages through the data communication middleware.

The environment simulation system implements both geographical and communication environment simulation subsystems. In the geographic environment simulation subsystem, the geographic data management module is responsible for storing, updating and rendering the terrain and maps for the UAV swarms. The human-computer interface involves the operation and maintenance management module and the visualization module for allowing us to observe the interactions between the UAVs and the environment, while the specific human-intervened control messages are fed directly into the data communication middleware and delivered to the UAV models. In the communication environment simulation subsystem, the background electromagnetic source management module simulates the behaviour of other emitters than the UAV communication devices, e.g. the interferers. Then, the effects of the terrain on communication channel prorogation will be evaluated by the communication effects computation module, which outputs the instantaneous channel matrix. The channel matrix management module would extract sub-matrix to corresponding UAVs, which would be resolved into signal-to-interference-noise power ratio, packet error ratio or other channel quality metrics.

We adopt Robot Operating System (ROS) [19] to provide the data communication middleware between the environment simulation system and the UAV simulation system. In the current implementation, the interferers are not considered, and the swarm-robot communication analysis (SRCA) tool proposed in [20] is adopted to compute the communication matrix in the environment simulation system and resolute packet loss ratios between each pair of UAVs, which provides real-time lossy communication channels for the UAV simulation systems. The basic sensing and actuator models in the UAV model are implemented along with the quadrotor UAV model in Gazebo simulator [21]. Swarm behaviours implemented in the swarm behaviour control module are used to provide various communication environments.

Through the above implementation, a team of UAVs and their interactions with the geographic and communication environments may be simulated. Arbitrary network topologies and lossy channel conditions may be configured, providing a flexible simulation platform for the data sharing algorithms. With the aid of the loose-coupling ROS middleware, it is convenient to upgrade the simulation platform to incorporate more realistic communication channel matrix computation, UAV models and advanced UAV swarm algorithms.

V. EXPERIMENTAL RESULTS AND ANALYSIS

We simulate and analyze the adaptive consensus data sharing algorithm in dynamic communication environments, and compare its convergence rate and payload costs with the lazy and eager algorithms. The transmission frequency of the request and data messages is set to 2Hz. The transmission mode we choose is the Mode 2 in Table II of [14]. The UAV identifier in request messages is 2 bytes, the data message for each request data is 8 bytes, and the total per-round message payload bytes required for this implementation is described by $\sum_{i=1}^{m} 2r_i + \sum_{i=1}^{m} 8d_i$, where m is the number of UAVs, r_i is the number of data requests by UAV i, and d_i is the number of data tuples to be sent.

A. DYNAMIC HOMOGENOUS LOW-LOSS AND HIGH-LOSS NETWORK SCENARIOS

In order to test the dynamic homogenous communication environment, a swarm of 8 UAVs are placed equidistantly on the circumference, so that the channel quality between any two UAVs may be assumed equal.

In the dynamic homogenous low-loss scenario, the range of packet loss rate is from 20% to 70%. The packet loss rate starts with 70% and all UAVs move towards the centre of the circle simultaneously, achieving a reduced packet loss rate along the way. Figure 5(a) shows the initial position of the swarm in Gazebo. The triangles on the graph indicate the positions of UAVs, inside the circle is the range of motion, and the arrows point to the movement directions.

In the dynamic homogenous high-loss scenario, the range of packet loss rate is from 70% to 90%. The packet loss rate starts with 90% and all UAVs move towards the opposite direction from the circle center simultaneously, but the deflation of the circle stops at the packet error rate of 70% and the UAVs start moving in the opposite direction. The portion between two dashed circles in Figure 5(b) is the range of motion.

Table 1 shows the average number of communication rounds and average total message payload bytes of per UAV, which is acquired for the lazy, eager and adaptive algorithms.

As shown in the 1-st and 2-nd rows of Table I, the performance of the lazy and eager algorithm is similar to that in a static communication environment. In the low-loss scenario, the adaptive algorithm performs close to the lazy algorithm, achieving a much less payload cost and a slightly longer convergence time than the eager algorithm. Although both the adaptive algorithm and eager algorithm achieve a full diversity order, the number of cooperative transmitters in the eager algorithm is in general larger than that in the adaptive algorithm. Therefore, a faster convergence rate may be achieved by the eager algorithm at the cost of a higher payload.

In this high-loss scenario, the eager algorithm and the adaptive algorithm perform similarly in both convergence and total payload bytes, and are superior to the lazy algorithm. In this advantage scenario of the eager algorithm, the performance of the lazy and eager algorithm is consistent with that in a static and high-loss communication environment, and both the convergence and payloads of the adaptive algorithm are very close to that of the eager algorithm.

Table I
EXPERIMENTAL RESULTS IN DIFFERENT REALISTIC NETWORK SCENARIOS

Scenario	Algorithm	Avg Convergence Rounds	Avg Total Payload Bytes
Homogenous Low-loss	Lazy	2.94	17.50
	Eager	2.68	48.88
	Adaptive	**3.13**	**26.30**
Homogenous High-loss	Lazy	40.38	425.00
	Eager	11.26	184.35
	Adaptive	**13.83**	**185.25**
Heterogenous swarm fusion and static within-swarm formation	Lazy	15.39	182.88
	Eager	7.24	150.04
	Adaptive	**10.04**	**137.44**
Heterogenous swarm fusion and dynamic within-swarm formation	Lazy	18.95	144.56
	Eager	9.17	122.80
	Adaptive	**9.96**	**98.14**

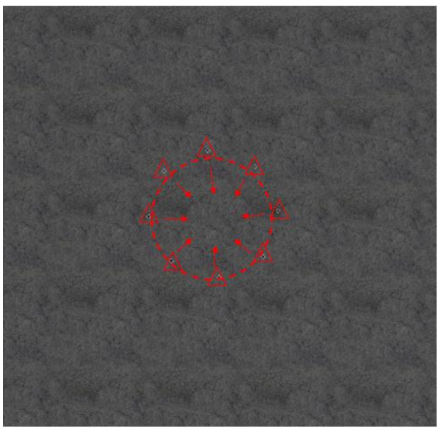
B. DYNAMIC HETEROGENOUS NETWORK SCENARIOS

In order to evaluate the data consensus algorithms in more sophisticated network scenarios, the interactions between different UAV swarms are considered. Without loss of generalization, data consensus behaviours during the fusion of two UAV swarms are investigated.

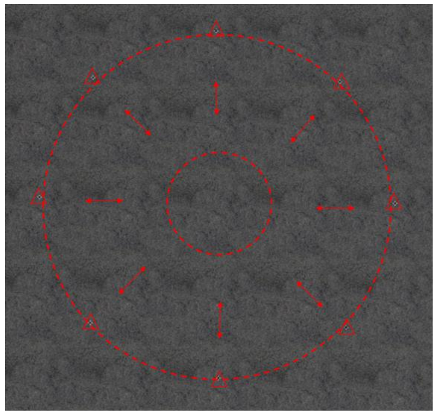
In the first heterogenous swarm fusion scenario, each swarm contains 5 UAVs. The two swarms move towards each other while maintaining formations within the swarm. The UAVs within the same swarm are experiencing low-loss channel quality, and the channel between UAVs across different swarms are of high-loss. The arrows in Figure 5(c) indicates the directions of swarm motions.

In the second heterogenous swarm fusion scenario, a single UAV and a swarm of 9 UAVs move towards each other, meanwhile the 9 UAVs inside the swarm are gradually approaching each other. The arrows in Figure 5(d) indicates the directions of swarm motions and the internal status of the swarm.

As shown in the 3-rd and 4-th rows of Table 1, the behaviours of the three algorithms are similar to those in the high-loss scenarios. Due to the limited space of the manuscript, observations of more scenarios are not included here, but it may be concluded that as long as some channels between UAVs experience high-loss, the convergence of the eager algorithm dominates the lazy algorithm, while the adaptive algorithm performs very close to the eager algorithm. Meanwhile, the total payload costs required for the adaptive algorithm is lowest, showing a more beneficial trade-off between convergence rate and payload cost.



(a)



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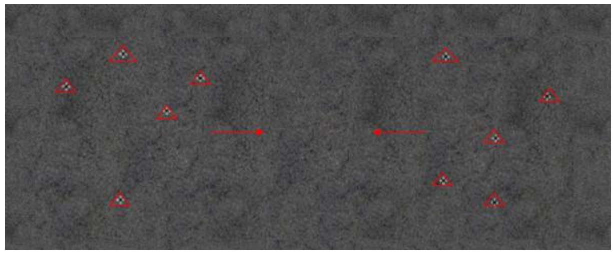
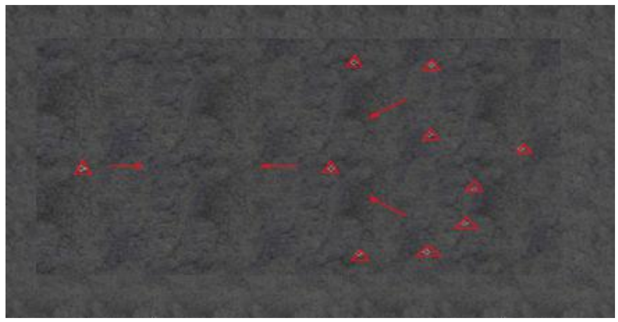


(c)



(d)

FIGURE 5. The initial positions of the UAV swarms in Gazebo in (a) homogenous low-loss scenario, (b) homogenous high-loss scenario, (c) heterogenous swarm fusion and static within-swarm formation, (d) heterogenous swarm fusion and dynamic within-swarm formation. The dashed circles indicates the range of motion, while the arrows indicates the movement of the UAVs.

VI. CONCLUSIONS

In this paper, we first compare the performance of the lazy and eager consensus data sharing algorithms in dynamic homogenous network scenarios. By transforming the data-sharing process into a sequence of transmitter selection, the adaptive consensus data sharing algorithm is proposed, adopting the best transmitter selection scheme. Then we design and implement a UAV swarm simulation platform, and set up dynamic homogenous and heterogenous network scenarios to analyse the performance of the data consensus sharing algorithms. It is shown show that the proposed adaptive algorithm may achieve a better trade-off between convergence rate and payload costs than the eager and lazy algorithms in various dynamic network scenarios.

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Yanqi Zhang received her B.S. degree in Hunan University in 2015 and M.S. degree in College of Computer in 2018 from National University of Defense Technology (NUDT), Changsha, P. R. China. Her main research interests include wireless network protocols, multi-robot systems and simulations.

Bo Zhang received his Ph.D. degree in Southampton Wireless Group, University of Southampton, UK, in 2015. He is now an associate professor in Artificial Intelligence Research Center, National Innovation Institute of Defense Technology, China. His research interests in cognitive communication and networking for robot systems. He has published more than 40 journal and conference papers. He is a principal investigator for three national foundation granted projects.

Xiaodong Yi received the Ph.D. degree in computer science from National University of Defense Technology. He now is a professor in the National Institute of Defense Technology Innovation, China. He has been devoted to Kylin operating system, which was used in Tianhe supercomputers, for over 10 years. His research interests include operating system, high performance computing, robotics software, etc.

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Jiankang Zhang received the B.Sc. degree in Mathematics and Applied Mathematics from Beijing University of Posts and Telecommunications in 2006, and the Ph.D. degree in Communication and Information Systems from Zhengzhou University in 2012. Dr Zhang was a lecturer from 2012 to 2013 and an associate professor from 2013 to 2014 in School of Information Engineering, Zhengzhou University. From 2009 to 2011, Dr Zhang was a visiting PhD student in the School of Electronics and Computer Science, the University of Southampton, UK. From 2013 to 2014, he was a postdoctoral researcher in the McGill University, Canada. Currently, he is a Senior Research Fellow in the University of Southampton, UK. Dr Zhang is a recipient of a number of academic awards, including Excellent Doctoral Dissertation of Henan Province, China, Youth Science and Technology Award of Henan Province, China. His research interests are in the areas of wireless communications and signal processing, aeronautical communications and broadband communications. He serves as an Associate Editor for IEEE ACCESS and a guest editor of a special issue on EURASIP Journal on Advances in Signal Processing.