Decentralized Task Assignment based on Information Fusion in Communication-Constrained Environments

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Abstract. In communication-constrained environments, the wireless communication quality of unmanned aerial vehicle (UAV) swarms is unstable. This paper proposes an information fusion strategy (IFS) based on information integrity and authenticity for the task assignment problem in communication-constrained environments. The proposed IFS is embedded into the classical sequential and G-Prim decentralized task assignment algorithms, and the two improved variants with the proposed IFS are denoted as Seq-IFS and G-Prim-IFS, respectively. The Gilbert-Elliott (G-E) model, which can model burst errors and bandwidth saturation, is adopted to describe unreliable communication channels. A series of test instances with different swarm sizes and different levels of communication channel reliability are used to compare the performances of Seq-IFS and G-Prim-IFS with their original forms. Numerical experimental results demonstrate that the Seq-IFS and the G-Prim-IFS outperform their original versions significantly in the majority of test instances, especially in cases with low communication channel reliability.

Keywords: task assignment, communication-constrained environments, information fusion, information integrity, information authenticity, Gilbert-Elliott model

1. INTRODUCTION

Unmanned aerial vehicle (UAV) swarms have a wide range of civilian and military applications due to their excellent performance, efficiency, and flexibility. For example, UAV swarms can be used to perform search and rescue, surveillance and reconnaissance, and firefighting missions [1]. Besides, several countries worldwide have proposed new warfare styles based on characteristics of UAV swarms. Recently, the mosaic warfare concept was proposed by the Strategic Technology Office (STO) [2]. A swarm of relatively low-cost UAVs is used to form an effective kill network. According to battlefield conditions and requirements, UAV swarms can be rapidly constructed in a self-coordinated and adaptive manner. If some UAVs of the swarms are destroyed, the remaining UAVs can dynamically reorganize and automatically respond to combat requirements.

Task assignment is one of the most popular research branches in the field of UAV swarms. UAV swarms are usually used in complex environments. Environmental factors such as signal fading, weather, obstacles, the distance between UAVs, and interference might make the communication of swarms fragile and unreliable [3]. They will lead to communication degradation scenarios such as packet loss, delay, etc. Since wireless communication between UAVs is employed in coordinating task assignments and verifying mission completion, unreliable communication could degrade swarm performance significantly. Improving the performance of task assignment is the key to overcoming the ineffectiveness of UAV swarms in communication-constrained environments. In short, it is of great research value to maximize the effect of task assignment in UAV swarms and to optimize the swarm performance.

There are two main categories of task assignments: centralized and decentralized. Centralized task assignment algorithms adopt the notion of a leader UAV, and the leader UAV would compute and assign tasks for UAVs. While in decentralized task assignments, each UAV can compute and assign their own tasks. In complex communication-constrained environments, the performances of both types of assignment algorithms degrade significantly. Centralized task assignment algorithms are more susceptible to packet losses than decentralized ones. It is possible to maintain a certain level of performance in degraded communication environments by designing reasonable coordination mechanisms. Typical approaches to decentralized task assignments are multi-agent intelligent decision strategies and market mechanisms (contracts/bidding) [4]. Specifically, market-based approaches (e.g., auction algorithms) constitue a critical branch of decentralized task assignment algorithms for UAV swarms. The core of decentralized assignments is conflict resolution using communication negotiation [5]. The performance of an auction-based algorithm was compared with other heuristic-based task selection strategies in [6] and it was eventually concluded that the auction-based algorithm improved the completion time by 30 to 60% compared with other heuristic-based multi-agent decision strategies.

The parallel auction[7], the sequential auction [8], the Prim allocation and its generalization [9] (denoted as G-Prim) are widely used to solve various real-world task assignment problems.

In the case of communication degradation, significant degradation of performance might occur. A UAV swarm communication method was proposed in [10] for the task assignment problem in an environment with low bandwidth and single-channel unreliable communication. P.B. Sujit and J.B.Sousa proposed an algorithm based on behavioral coordination for the problem of communication failures within UAV swarms [11]. Numerical results showed that the swarm system with the algorithm performed close to that of the system with no communication failures. In a search game where two multi-agent teams compete to find a stationary target at an unknown location, closed-form expressions are found for the probability of winning the game as a function of team sizes and the existence or absence of communication within each team [12]. In summary, it can be concluded that the key to improving the performance of distributed tasking is the completeness and authenticity of information in communication. Therefore, an information fusion strategy is proposed in this paper for improving the performance of UAV swarms in communication-constrained environments.

The main contributions of this paper are as follows: (1) An information fusion strategy (IFS) is proposed for the task assignment problem of UAV swarms in communication degraded environments. (2) The proposed IFS is embedded into the classical sequential auction and the G-Prim auction, resulting in two improved algorithms named Seq-IFS and G-Prim-IFS. (3) Considering different combat resources and communication channel reliability levels, 9 test instances were designed to compare the performance of four algorithms. Numerical experiments verified the effectiveness of the proposed information fusion strategy.

This paper is organized as follows. Section 2 describes the task requirements and the communication constraints. Then, we establish the model of task assignment for UAV swarms. Section 3 presents details of the information fusion strategy (IFS) and the improved algorithms embedded with the proposed IFS. Section 4 demonstrates a series of test instances and the comparisons between the improved algorithms, Seq-IFS and G-Prim-IFS, and their original versions. Section 5 concludes the paper and identifies future work.

2. PROBLEM FORMULATION

2.1. The Gilbert-Elliott (G-E) Model

The Gilbert Elliott (G-E) communication model [13], as shown in Fig. 1, is adopted to model communication-constrained environments. The G-E model assumes two communication states: good and bad states. The probability of establishing valid communication in the good communication state is denoted by p_g, and that in the bad communication state is denoted by p_b. The probability of staying in the good communication state is

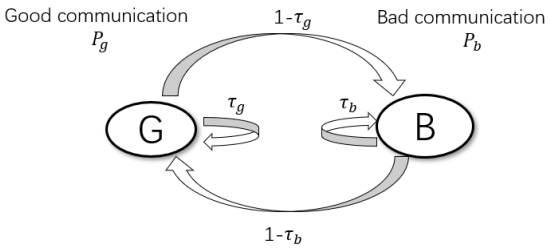


Fig. 1 Gilbert-Elliott communication model.

τ_g, and that in the bad communication state is τ_b. The G-E model can simulate UAV swarms in an unstable communication condition, switching between good and bad communication states. It has been shown that the G-E model presents an accurate approximation of communication channel conditions in practical applications.

2.2. Task Assignment under Communication Constraints

This paper considers a set of fixed-wing UAVs to perform search and attack tasks in communication-constrained environments. The set of UAV swarms and that of targets are denoted as $U = \{U_1, U_2 \ldots, U_M\}$ and $T = \{T_1, T_2 \ldots, T_N\}$, respectively. M and N represent the UAV swarm size and the amount of task targets, respectively. For each target $T_j \in T$, define its position as pos_j^t; the value w_j indicates the priority in selecting the target, the higher the value is, the more priority is given in the allocation; the value d_j indicates the defense capability of the target. This work considers the situation where each target corresponds to one task only and each UAV can only execute one task. So it can be simply understood that d_j is the number of UAVs needed to complete the attack task.

For each UAV $U_i \in U$, define its position as pos_i^u, it velocity as vel_i^u, and its communication radius as R. In complex environments, the communication quality between UAVs varies over time. We denote the communication quality between U_i and U_m as $p_{im}(\mathrm{t})$. The minimum reliable communication quality of UAVs is P. Therefore $\Gamma_i(t) = \{m \in U \mid |pos_i^u - pos_m^u| \le R, p_{im}(\mathrm{t}) \ge \mathrm{P}\}$ is the set of neighboring UAVs that U_i can reliably communicate with at time t.

The completion rate for the attack task upon the targets is an important performance indicator for task assignment. Each target has an value indicating the priority sequence when attacking. The fitness function describing task assignment performance is as in (1).

$$\begin{gathered} S = \sum_{j=1}^{N} S_j = \sum_{j=1}^{N} \omega_j / \exp(y_j) \\ if\ \chi_j > d_j, y_j = \chi_j - d_j \\ else\ y_j = 2 \times (d_j - \chi_j) \end{gathered} \tag{1}$$

In (1), the value w_j indicates the priority in selecting the target .exp(.) is the natural exponential function. S_j is the performance component relating to target T_j in the overall optimization. $\chi_j = \sum_{i=1}^{M} x_{ij}$ represents the number of UAVs actually assigned to target T_j in the

assignment, where $x_{ij} \in \{0,\ 1\}$ is a decision variable indicating whether U_i is assigned to T_j, with $x_{ij} = 1$ indicating "yes" and $x_{ij} = 0$ indicating "no", constituting the assignment matrix $X = [x_{ij}]_{M\times N}$. When the actual number of assigned UAVs is less than that of required UAVs, the penalty is greater. When the assigned amount is greater than the required amount, the task is completed with waste of combat resources, so the penalty is smaller.

$$0 \le \forall \chi_j \le N_j \times d_j \tag{2}$$

The constraint in (2) indicates that the actual number of UAVs assigned to each target cannot exceed N_j, and in this paper we take $N_j = 2$. The actual number of UAVs assigned cannot be greater than twice the number of UAVs required.

3. DECENTRALIZED TASK ASSIGNMENT BASED ON INFORMATION FUSION

3.1. Information Fusion Strategy (IFS)

In communication-constrained environments, wireless communication between UAVs could be severely limited. Communication delays and packet loss may occur, resulting in loss of important task information. It is possible that two UAVs within communication ranges could not establish stable communication due to insufficient channel quality. It can lead to information loss in sending and receiving messages. During the search phase, targets found by certain UAVs might not be advertised to their neighboring UAVs due to the low quality of communication. These occurrences would lead to inconsistent situational awareness, thus degrading the assignment performance.

In terms of communication and inspired by the transmission control protocol (TCP) and the user datagram protocol (UDP), there are as least two ways to deal with poor communication in auctions.

(1) The auctioneer waits until hearing from each agent in each round.

(2) The auctioneer waits in each round for a specific amount of time, and those UAVs that are unable to communicate will not submit bids.

In reality, it is usually impossible to know whether or not a particular UAV is within communication range, so the second waiting style is chosen.

The concept of information fusion was considered in the basic framework of waiting. Information fusion is the union, correlation, and combination of data and information from multiple sources, in order to obtain more accurate estimations[14]. We treat each communication attempt as a separate information source. According to the communication mechanism within the UAV swarm, UAVs try to establish mutual communication at a certain frequency. This means that each communication attempt would have partial information transfer. Fusion of fragmented information obtained from multiple communication attempts in poor communication conditions is the main idea of the proposed information fusion strategy (IFS). Let the auctioneer a records the communication lists of all communication attempts, with a limit to the number of valid communication attempts. If auctioneer a 's v th communication attempt occurs at moment t_v, then this communication list is described as $r_{a,v} = \Gamma_a(t_v)$.

Considering the information errors introduced by different communication attempts, we introduce the concept of authenticity for each information fragment. The most recent W messages are recorded and fused as in $R_a = r_{a,1} \cup r_{a,2} \cup \ldots \cup r_{a,v} \cup \ldots \cup r_{a,W}$ and $L_a = \{p_i = n_i/W \mid i \in R_a\}$ (where n_i is the number of times i appears in message $r_{a,v}$). The fused information is used to improve the integrity and authenticity of messages received from communicable neighboring UAVs. Information integrity and authenticity directly affects the performance of assignment.

The IFS proposed in this paper is shown in Algorithm 1. Specifically, the auctioneer UAV a (auct. a In Algorithm 1) makes W communication attempts to all UAVs i in the swarm (lines 1-2). The information of each communication attempt of the auctioneer is integrated to obtain the estimation of complete information R_a and of authenticity level L_a (lines 3-4).

Algorithm 1 **Information Fusion Strategy**

on auct. a, **1: for** $v \in \{1 \ldots W\}$ **do**
on auct. a, **2:** **for** $i \in U$ **do**
on auct. a, **3:** $R_a \leftarrow R_a \cup r_{a,v}$
on auct. a, **4:** $L_a[i] \leftarrow n_i/W$

3.2. Decentralized Task Assignment Algorithm Improved with IFS

In this paper, the information fusion strategy is embedded into the classical sequential and G-Prim auction algorithms, resulting in the Seq-IFS and the G-Prim-IFS shown in Algorithm 2 and Algorithm 3.

We define the valuation function $V_{i,j}[j]$ of (3) as the difference between benefit $U_{i,j}$ and cost $C_{i,j}$. In (4), the cost function $C_{i,j}$ is the product of the UAV cost factor s, the target threat level K, and the target single-shot kill probability $P_{t_}$. In (5), the benefit function $U_{i,j}$ considers the UAV advantage coefficient μ_1, the UAV advantage P, the target value coefficient μ_2 ($\mu_1 + \mu_2 = 1,\ 0 \le \mu_1,\ \mu_2 \le 1$), the target value w_j, and the UAV single-shot kill probability P_t .The UAV advantage P, defined in (6), considers the distance advantage coefficient δ_1, the distance cost function F_d, the angular advantage coefficient δ_2, and the angular cost function F_q. When defining the distance cost function F_d in (7), D is the maximum distance that the UAV can reach and attack targets at, Δpos is the distance between the UAV and the target and is further defined in (10). In the angular cost function F_q in (8), $\Delta\theta$ is the angular difference between the UAV velocity direction and the bearing angle of the target relative to the UAV, as defined in (9).

$$V_{i,j}[j] = U_{i,j} - C_{i,j} \tag{3}$$
$$C_{i,j} = s \times K \times P_{t_} \tag{4}$$
$$U_{i,j} = (\mu_1 \times P + \mu_2 \times w_j) \times P_t \tag{5}$$
$$P = \delta_1 \times F_d + \delta_2 \times F_q \tag{6}$$
$$F_d = \exp\,(1 - |\Delta pos|/D) \tag{7}$$
$$F_q = \exp\,(1 - \Delta\theta/\pi) \tag{8}$$
$$\Delta\theta = < vel_i^u, \Delta pos > \tag{9}$$
$$\Delta pos = pos_j^t - pos_i^u \tag{10}$$

Algorithm 2 **Sequential Auction with IFS (Seq-IFS)**

1: **for** $j \in \{1 \dots N\}$ **do**
on auct.a, 2: $(R_a, L_a) \leftarrow Information\ Fusion\ Strategy$
on auct.a, 3: $a.Broadcast(j)$ to $i \in R_a$
on agent i, 4: **if** $i.Receive(j)$ **then**
on agent i, 5: $B_i[j] \leftarrow V_{i,j}[j]$
on agent i, 6: $i.Send(B_i[j])$
on auct.a, 7: **while** $time\ left$ **do**
on auct.a, 8: **if** $a.Receive(B_i[j])$ **then**
on auct.a, 9: $\tilde{B}_{i,j} \leftarrow L_a[i] \times B_i[j]$
on auct.a, 10: $\tilde{B}_{i,j}.rank \leftarrow \tilde{B}_{i,j}.sort(descending)$
on auct.a, 11: $h \leftarrow arg\ max_i S_j$
on auct.a, 12: $\tilde{X}_h \leftarrow \tilde{X}_h \cup \{j\}$
on auct.a, 13: $R_a \leftarrow Information\ Fusion\ Strategy$
on auct.a, 14: $a.Broadcast(h, j)$ to $i \in R_a$
on agent i, 15: **if** $i.Receive(h, j)$ **and** $i = h$ **then**
on agent i, 16: $X_i \leftarrow X_i \cup \{j\}$
on agent i, 17: $i.Send(C_{h,j})$
on auct.a, 18: $wait\ appropriate\ amount\ of\ time$
on auct.a, 19: **if not** $a.Receive(C_{h,j})$ **then**
on auct.a, 20: $X_a \leftarrow X_a \cup \{j\}$

The algorithmic description of the improved sequential auction algorithm, the Seq-IFS, is shown in Algorithm 2. Specifically, each round assigns one task, and there are N rounds of auctions (line 1). Auctioneer a *broadcasts* task information to all UAVs $i \in R_a$ that it can communicate to (including itself, lines 2-3). Each UAV i uses its own valuation function $V_{i,j}[j]$ to bid on task j, thus obtaining $B_i[j]$, and *sends* the price $B_i[j]$ to auctioneer a (lines 4-6). Auctioneer a waits for a preset time to receive the prices and process them in combination with authenticity $L_a[i]$, obtaining the auctioneer-aware price list $\tilde{B}_{i,j}$ (lines 7-9), and sorts list $\tilde{B}_{i,j}$ in descending order (line 10). Auctioneer a awards the task to the UAV h that maximizes S_j, and then *broadcasts* the award list X (lines 11-14). UAV i that is awarded the task in this round *sends* an acknowledgment message $C_{h,j}$ to auctioneer a after *receiving* the task (lines 15-17). Finally, auctioneer a assumes responsibility for the unacknowledged tasks (lines 18-20).

The improved G-Prim Auction algorithm, the G-Prim-IFS, is described in Algorithm 3. G-Prim-IFS is also an N-round auction. Unlike in Seq-IFS, multiple tasks j$\in \Theta_r$ are up to be auctioned each round in G-Prim-IFS. Each UAV i bids on the known multiple tasks and *sends* the highest bid to the auctioneer (lines 6-10). Auctioneer a selects the UAV h and the corresponding task j that maximizes S_j (lines 15-16). The rest of the procedure is similar to that in Seq-IFS.

Algorithm 3 **G-Prim Auction with IFS (G-Prim-IFS)**

1: **for** $j \in \{1 \dots N\}$ **do**
on auct.a, 2: $\tilde{B}_{i\dots M,1\dots N} \leftarrow -\infty$
on auct.a, 3: $\Theta_r \leftarrow \Theta / \Theta_{sold}$
on auct.a, 4: $(R_a, L_a) \leftarrow Information\ Fusion\ Strategy$
on auct.a, 5: $a.Broadcast(\Theta_r)$ to $i \in R_a$
on agent i, 6: **if** $i.Receive(\Theta_r)$ **then**
on agent i, 7: **for all** $j \in \Theta_r$ **do**
on agent i, 8: $B_i[j] \leftarrow V_{i,j}[j]$
on agent i, 9: $\hat{b}_{i,j} \leftarrow arg\ max_j B_i[j]$
on agent i, 10: $i.Send(\hat{b}_{i,j})$
on auct.a, 11: **while** $time\ left$ **do**
on auct.a, 12: **if** $a.Receive(\hat{b}_{i,j})$ **then**
on auct.a, 13: $\tilde{B}_{i,j} \leftarrow L_a[i] \times \hat{b}_{i,j}$
on auct.a, 14: $\tilde{B}_{i,j}.rank \leftarrow \tilde{B}_{i,j}.sort(descending)$
on auct.a, 15: $(h, j) \leftarrow arg\ max_{(i,j)} S_j$
on auct.a, 16: $\tilde{X}_h \leftarrow \tilde{X}_h \cup \{j\}$
on auct.a, 17: $R_a \leftarrow Information\ Fusion\ Strategy$
on auct.a, 18: $a.Broadcast(h, j)$ to $i \in R_a$
on agent i, 19: **if** $i.Receive(h, j)$ **and** $i = h$ **then**
on agent i, 20: $X_i \leftarrow X_i \cup \{j\}$
on agent i, 21: $i.Send(C_{h,j})$
on auct.a, 22: $wait\ appropriate\ amount\ of\ time$
on auct.a, 23: **if not** $a.Receive(C_{h,j})$ **then**
on auct.a, 24: $X_a \leftarrow X_a \cup \{j\}$
on auct.a, 25: $\Theta_{sold} \leftarrow \Theta_{sold} \cup \{j\}$

4. NUMERICAL EXPERIMENTS

4.1. Test Instances

This experiment sets the flight area to $2km \times 2km$; the UAVs in the swarm are fixed-wing UAVs with a communication radius of $R = 500m$; the initial positions of the UAVs are randomly generated within the interval $[-1\text{km}, -0.9\text{km}]$ along both axes; The number of targets is $N = 5$, the target defence capability is set as $d_j \equiv 3$ (i.e., three UAVs are needed to destroy each target); the target values are: $w_1 = w_4 = 7, w_2 = w_5 = 5, w_3 = 9$.

Considering the real-world combat scenarios with different amount of resources and different levels of communication channel quality, we designed 9 test instances. 30 experiments were conducted on each instance. In this paper, the M/N ratio is used to describe the power comparison. (e.g., 10 UAVs and 5 targets; 15 UAVs and 5 targets; 20 UAVs and 5 targets.)

For communication channel reliability, the G-E model adopts the parameter values shown in (11).

$$G-E\ model: \tau_b = 0.3,\ 0.6,\ 0.9 \quad while\ \tau_g = 0.5,\ p_g = 0.9,\ p_b = 0.3 \tag{11}$$

4.2. Parameter Settings

In the two improved algorithms with IFS, W is set to 20. The maximum simulation length is 5000 time steps. In the valuation function, the UAV advantage coefficient is $\mu_1 = 0.5$, the target value coefficient is $\mu_2 = 0.5$, the UAV single-shot kill probability is $P_t = 0.8$, the distance advantage coefficient is $\delta_1 = 0.5$, the angular advantage coefficient is $\delta_2 = 0.5$, the maximum attack distance for the UAV is $D = 0.6km$, the UAV cost factor is $s = 0.5$, the target threat level is $K = 0.5$, and the target single-shot kill probability is $P_{t_} = 0.6$.

In terms of task evaluation, the evaluation criteria selected in this paper are as follows.

i. The objective function as described in (1). It is the fitness function describing task assignment performance.

ii. The task completion rate $G = n/N \times 100\%$, where N indicates the number of targets, and n indicates the number of completed tasks.

Table. 1 Performance comparison of G-Prim, G-Prim-IFS, Sequential Auction and Seq-IFS in terms of assignment scores.

τ_b	UAV Swarm Size	G-Prim	G-Prim-IFS	Sequential Auction	Seq-IFS
0.3	10	16.127≈ (4)	16.203 (2)	**16.348≈ (1)**	16.140 (3)
	15	22.767§ (2)	19.207 (4)	21.245† (3)	**23.151 (1)**
	20	23.606≈ (4)	24.371 (2)	23.312≈ (3)	**24.700 (1)**
0.6	10	15.833† (3)	**17.232 (1)**	13.495† (4)	16.675 (2)
	15	22.044≈ (2)	21.322 (3)	12.702† (4)	**24.684 (1)**
	20	**24.848§ (1)**	22.988 (3)	16.161† (4)	23.774 (2)
0.9	10	6.317† (3)	**13.118 (1)**	1.412† (4)	10.509 (2)
	15	7.561† (3)	**19.816 (1)**	1.443† (4)	11.683 (2)
	20	12.635† (3)	**21.532 (1)**	1.843† (4)	13.919 (2)

4.3. Comparison Results

The algorithms used for comparison are the sequential auction, the G-Prim auction, and the two improved algorithms embedded with IFS, the Seq-IFS and the G-Prim-IFS. Communication constraints and assignment algorithms are programmed in a multi-agent simulation environment that contains cascaded control structures for the UAV swarm system.

A total of nine test instances designed under three different combat resource ratios and three communication channel reliability levels were used. 30 experiments were conducted on each instance. Table. 1 shows the performances of G-Prim, G-Prim-IFS, sequential auction, and Seq-IFS on each test instance in terms of assignment scores(average value). Symbols †, §, and ≈ indicate that the performance of the IFS-variant is better than, worse than, and similar to that of the original algorithm. The data in bold represents the best performance among the four algorithms, and the performance ranking is shown in parentheses in descending order. From Table. 1, we can see that the performances of the algorithms are close when the communication condition is good ($\tau_b = 0.3$). When the communication condition is slightly worse ($\tau_b = 0.6$), the sequential auction algorithms embedded with the information fusion strategy have significantly better performance than the original one. When the communication condition is poor ($\tau_b = 0.9$), we can clearly see that both improved algorithms (G-Prim-IFS and Seq-IFS) show substantial performance improvements. The G-Prim and its variant perform better than the sequential auction and its variant overall, thus verifying the performance conclusion in [8].

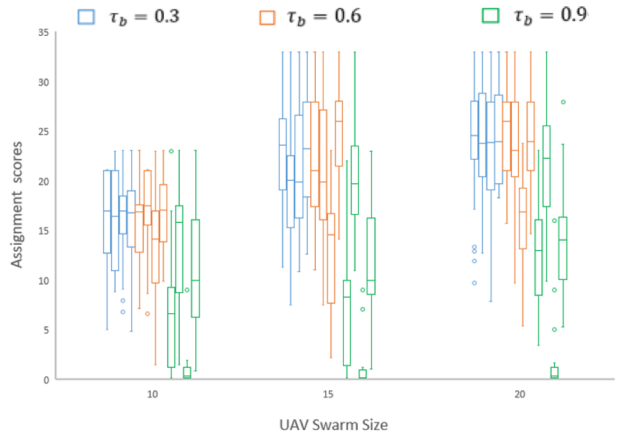


Fig. 2 Box plots of algorithm performances under thirty runs of each algorithm on each test instance in terms of assignment scores. In each group of same-colour results, G-Prim, G-Prim-IFS, sequential auction and Seq-IFS are arranged from left to right.

Fig. 2 shows the box plots of task assignment performances S of thirty runs of each algorithm under each test instance. In each group of same-colour results, G-Prim, G-Prim-IFS, sequential auction and Seq-IFS are arranged from left to right. It can be clearly seen from Fig. 2 that the improved algorithms embedded with IFS decisively outperform the original algorithms. Performance improvements are more significant in environments with low communication reliability.

In terms of task completion, Table. 2 summarizes the performance comparison of G-Prim, G-Prim-IFS, sequential auction, and Seq-IFS regarding the task completion rate(average value). Symbols †, §, and ≈ indicate that the task completion rate of the IFS-variant is better than, worse than, and similar to that of the original algorithm. Data in bold represent the best completion rates among the four algorithms, and the mean completion rate ranking is shown in parentheses in descending order.

Fig. 3 summarizes the task completion rates under different G-E model settings(average value). The first three rows are for $\tau_b = 0.3$, the middle three rows for $\tau_b = 0.6$, and the last three rows for $\tau_b = 0.9$, respectively. It can be seen from Fig. 3 that G-Prim-IFS has the highest task completion rate in most test instances, except in the instance ($\tau_b = 0.3, M = 15$) where Seq-IFS has the highest task completion rate. The improved algorithms embedded with the IFS consistently have higher task completion rates than their original versions. The improvements in task completion rates are less significant when the communication reliability is high ($\tau_b = 0.3$). When the communication channel reliability is bad ($\tau_b = 0.9$), the improvements in algorithm task completion rates are highly significant. In the instance ($\tau_b = 0.9, M = 20$), the task completion rate of G-Prim improves from 33% (without IFS) to 86% (with IFS).

Table. 2 Performance comparison of G-Prim, G-Prim-IFS, Sequential Auction, and Seq-IFS in terms of the task completion rates.

τ_b	UAV Swarm Size	G-Prim	G-Prim-IFS	Sequential Auction	Seq-IFS
0.3	10	48.00%† (2)	**52.00**%(1)	43.33%(4) †	46.67%(3)
	15	70.67%† (3)	72.00%(2)	61.33%(4) †	**76.67**%(1)
	20	75.33%† (3)	**88.67**%(1)	70.00%(4) †	78.67%(2)
0.6	10	41.33%† (3)	**54.67**%(1)	34.67%(4) †	45.33%(2)
	15	69.33%† (3)	**80.67**%(1)	32.67%(4) †	72.67%(2)
	20	73.33%† (3)	**84.00**%(1)	43.33%(4) †	75.33%(2)
0.9	10	14.00%† (3)	**48.00**%(1)	2.00%(4) †	25.33%(2)
	15	18.00%† (3)	**74.00**%(1)	2.67%(4) †	30.67%(2)
	20	33.33%† (3)	**86.00**%(1)	3.33%(4) †	36.00%(2)

5. CONCLUSION

In this paper, we study the problem of task assignment for UAV swarms in communication-constrained environments. The information fusion strategy (IFS) is proposed based on information completion and authenticity. The Seq-IFS and G-Prim-IFS algorithms are designed by embedding the proposed IFS into the classical sequential and G-Prim auction algorithms. The assignment performances and task completion rates of two improved variants and their original versions are evaluated and compared under different communication channel reliability levels and combat resource ratios. Numerical experiments show that the proposed IFS can improve the information integrity and authenticity in poor communication conditions, leading to betther assignments and higher task completion rates. In particular, it significantly improves algorithm performances and task completion rates in tests with low communication channel reliability levels. In the test instance with $\tau_b = 0.9$ and the UAV swarm size of 20, the task assignment score of G-prim improves from 12.635 to 21.532, and that of sequential auction improves from 1.843 to 13.919, by embedding the IFS. In this test instance, the task completion rate of G-Prim improves from 33% to 86%.

IFS in this paper focuses on the problem of information loss when communication between UAVs is unstable. Future work will pay more attention to the information loss problem in the searching stage. The performance of UAV swarms in complex environments could be improved from different aspects.

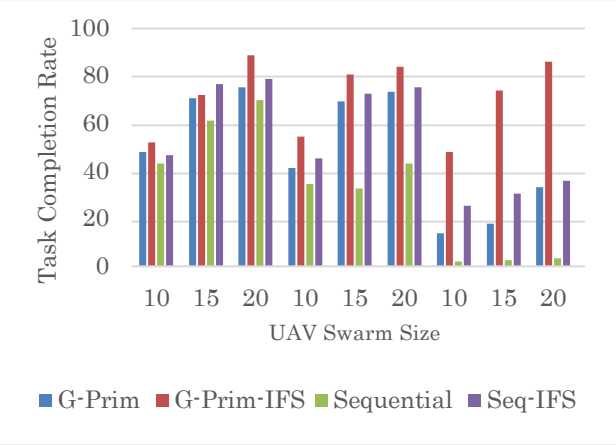


Fig.3 Histogram of algorithm performances under thirty runs of each algorithm on each test instance in terms of task completion rates.

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