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Strategy dominance mechanism of autonomous collaboration in unmanned swarm within the framework of public goods game

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Abstract: The key advantage of unmanned swarm operation is its autonomous cooperation. How to improve the proportion of cooperators is one of the key issues of autonomous collaboration in unmanned swarm operations. This work proposes a strategy dominance mechanism of autonomous collaboration in unmanned swarm within the framework of public goods game. It starts with the requirement analysis of autonomous collaboration in unmanned swarm; and an aspiration-driven multiplayer evolutionary game model is established based on the requirement. Then the average abundance function and strategy dominance condition of the model are constructed by theoretical derivation. Furthermore, the evolutionary mechanism of parameter adjustment in swarm cooperation is revealed via simulation, and the influences of the multiplication factor r, aspiration level α, threshold m and other parameters on the strategy dominance conditions were simulated for both linear and threshold public goods games (PGGs) to determine the strategy dominance characteristics; Finally, deliberate proposals are suggested to provide a meaningful exploration in the actual control of unmanned swarm cooperation.

Keywords: unmanned combat swarm, autonomous collaboration, strategy dominance, multi-player public goods game (PGG).

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1. Introduction

Continuing advances from a third wave of artificial intelligence (AI) has resulted in the development of “swarm evolutionary intelligence” from “individual autonomous intelligence”, which has become one of the key characteristics of AI 2.0. In particular, unmanned combat swarms (unmanned land vehicle swarms [1–3], unmanned surface warship swarms [4–6] and unmanned aerial vehicle (UAV) swarms [7–10]) have received unprecedented attention in the military domain. For example, the US military considers swarm operations to be a disruptive technology that can change combat rules.

Unmanned swarms are currently primarily controlled in centralized and autonomously cooperative ways. Centralized control relies on orders from the ground station and pre-programming of UAVs, whereas autonomously cooperative control requires a swarm to make autonomous decisions based on specific situations. Unmanned swarms are faced with the extreme difficulty of maintaining communication and a sharp increase in the probability of communication failure in a complex electromagnetic environment, especially when going deep behind enemy lines [11]. As centralized control can fail under these circumstances, unmanned swarms must be able to carry out a targeted emergency response based on the status of both the enemy and our own forces, the battlefield environment and other factors, while continuing to fulfil the military missions depending on intra-swarm self-organization and self-collaboration.

The global optimal allocation of resources is an essential component of the autonomous collaboration of unmanned swarms and profoundly impacts the combat effectiveness. However, the individual interests/payoff of each intelligent unit need to be balanced against the global operational requirements of the entire swarm. Considering a fire strike as an example, intelligence enables each combat unit to make independent decisions. Units

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ensure battlefield survivability by carefully controlling the amount of ammunition fired or launched. However, the higher the firepower support one unit provides, the more beneficial the overall combat effectiveness of the swarm is. A conflict between the swarm and individual units can result in a "tragedy of public resources" [12]. This conflict is a difficult and urgent issue for both swarm control and practical training/operations and warrants the design of a reasonable mechanism for the autonomous collaboration of swarms.

The essence of swarm self-collaboration is the unity of opposites among individuals, that is, attaining the equilibrium of payoff. Evolutionary game theory [13,14] has opened the door to realizing swarm self-collaboration. Specifically, the public goods games (PGGs) [15] provides a theoretical framework within which the mechanism of self-organization can be elucidated to effectively control swarm conflicts. Research on methods to improve the proportion of collaborators in the game and obtain a strict strategy dominance condition is an important prerequisite to resolving the "tragedy of public resources" and realizing the autonomous collaboration of unmanned swarms.

A research team led by Professor Nowak at Harvard University [16,17] used mathematical derivations and simulations to develop an evolutionary dynamics-based strategy dominance condition of the multiplayer game under a weak selection intensity. Antal et al. [18] proposed a strategy dominance condition for a two-player game that was subsequently used to determine the strategy dominance conditions under any selected intensity for a multiparty game based on imitation dynamics [19,20], thereby extending the results of Nowak et al. However, Nowak et al. considered evolutionary dynamics [16,21], Roca et al. determined the strategy dominance condition for an aspiration-driven updating rule [22]. Du et al. applied the results of Tarnita et al. [23] in conjunction with a statistical analysis and computer simulation to find that the average abundance was independent of the aspiration level under a weak selection intensity [24]. Furthermore, Du et al. extended this theoretical result to determine the strategy dominance condition for the multiplayer game under a weak selection intensity [25,26].

The aforementioned studies have laid a solid foundation for studying self-organization and self-collaboration of swarms. However, the results of these studies primarily apply to common evolutionary game models and not the PGGs, which is the basic theoretical framework for investigating the strategy dominance condition of unmanned swarms and addressing the "tragedy of public resources". In addition, no studies with military applications have been performed. Existing PGGs mostly apply to environmental pollution [27], urban public resource development [28], cultural evolution [29], etc. Given the unique attributes of the military and the novelty of warfare mode of unmanned swarm, few results of the aforementioned studies are relevant to military applications.

We have also conducted an exploration on the self-collaboration mechanism of unmanned swarm. We have theoretically derived the average abundance function for a multiplayer PGGs and analyzed the influences of relevant parameters on the average abundance, and the relevant achievements can be referred to [30–33]. On the basis of the average abundance function in [31], we further derive the strategy dominance conditions of linear and threshold PGG. Furthermore, the influences of the multiplication factor, aspiration level, threshold and other parameters on the strategy dominance conditions were simulated in this research. The collaborative of unmanned swarms was modeled in this study based on the aspiration-driven updating rule and the multiplayer evolutionary game framework. The average abundance function was then used to derive the collaborative strategy dominance condition of the multiplayer evolutionary game, and the strategy dominance conditions of linear and threshold PGGs were obtained. The corresponding characteristics were analyzed, and the results were used to make the recommendations for preventing the "tragedy of public resources" and implementing the autonomous collaboration of unmanned swarms.

The innovative work of this study includes that the analytical framework for autonomous collaborative behavior in unmanned swarms is put forward, relationship between the concepts of the unmanned swarm and the multiplayer public goods game is proposed and the strategy dominance conditions of linear and threshold PGGs are obtained respectively.

2. Military requirements

The autonomous collaboration of unmanned swarms involve three key components, i.e., emergent intelligence, the construction of information network and the design of coordination mechanism. These three components form the basic framework of the autonomous collaborative behaviour of unmanned swarms. The relationship between these three components is shown in Fig. 1. The construction of information network is not a central consideration in this study and is only described briefly with grey font.

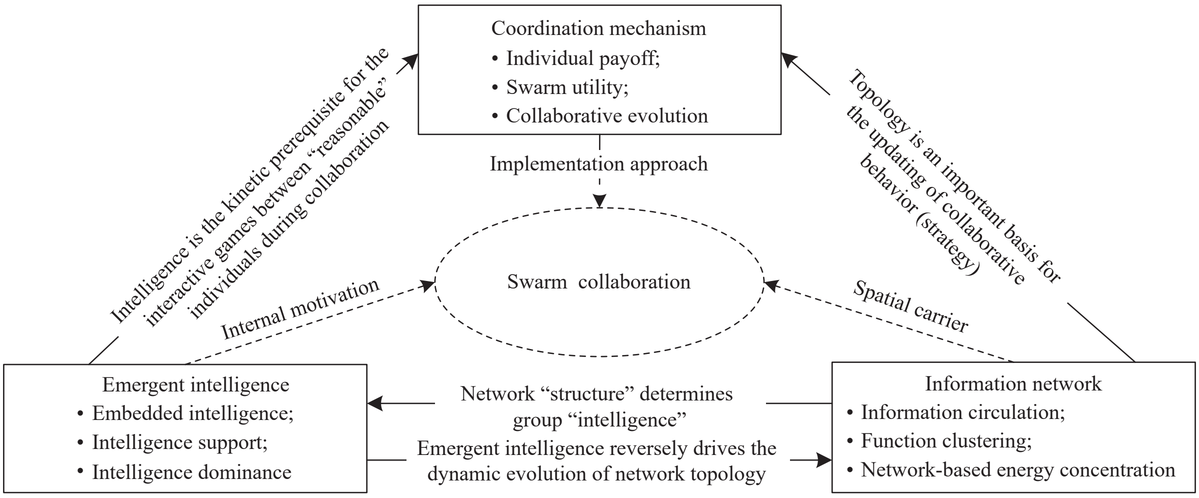


Fig. 1 Analytical framework for autonomous collaborative behaviour in unmanned swarms

The emergent intelligence of a swarm from individuals provides the internal motivation for the autonomous collaborative behaviour of the swarm. The information network is the space in the swarm where information interactions take place and the carrier of autonomously collaborative behaviour. The coordination mechanism is the ultimate pathway to realize swarm self-collaboration. Emergent intelligence and the coordination mechanism are discussed in detail in the following sections.

2.1 Emergent intelligence

In unmanned swarm, units with "intelligence" not only passively accept preset instructions, but most importantly, they optimally coordinate and organize their own resource, cost, behavior and other factors through the processes of unmanned autonomy, senior driven, collaborative interaction, utility optimization, capability generation and so on. At the swarm level, higher-level intelligence beyond individual intelligence emerges, and finally realizes the optimization of the overall utility of the swarm.

Intelligence includes the "single intelligence" of individuals and the "emergent intelligence" of swarms and is a prerequisite for the distributed autonomous control of swarms. Using unmanned swarms to carry out military missions based on a predetermined plan has inherent shortcomings. The complex battlefield environment corresponds to a continuously changing scenario. Implementing micromanagement on a single unmanned platform can severely strain resources such as communication. That is, the responsive control of many unmanned platforms is beyond the current technology, cognition and decision-making capabilities of human beings, with a high probability of leading to the failure of combat operations. Hence, more decision-making and action rights must be transferred to the autonomous control system of unmanned swarms to enable an unmanned platform to independently coordinate its own decision-making to promote behaviours that enable the swarm to realize its operational goals.

The Defense Science Board of the US Department of Defense identified intelligence and autonomy as the core capabilities of the U.S. military's unmanned systems and analyzed the benefits of intelligence and autonomy to UAVs, unmanned ground systems (UGSs), unmanned marine vehicles (UMVs) and unmanned space systems (USSs) [34]. Unmanned swarm operation systems will require a high level of perception, analysis, planning, decision-making and execution capabilities in the future to autonomously perceive a battlefield situation, plan combat missions, carry out combat actions, coordinate combat actions and evaluate combat effects.

Although the individual in swarm has intelligence, the achievement of the optimal overall utility at the swarm level is not made overnight, but an iterative and self-organizing evolution process. Individuals must modify and improve strategies through a large number of repeated game processes, learning, imitation and trial and error, so as to constantly adapt to the external environment and finally achieve the optimal overall utility of the swarm. In the military field, from the long-term development of war form, the generation of intelligence and its impact on combat is also a long-term development process. Unmanned combat utilizing a remote-control mode for human-computer interaction has progressed to a collaborative mode characterized by man-machine integration and is developing towards an autonomous collaboration mode featuring human-machine integration [35–37]. Emergent intelligence in unmanned swarms could evolve from the "embedding of intelligence" with man playing the leading role supplemented by machines to "intelligent support" featuring unmanned autonomy and finally to "intelligence dominance" with bionic autonomy and autonomous attack and defence by swarms.

2.2 Coordination mechanism

In the military field, the winning mechanism of intelligent warfare is more manifested in "intelligence" and "autonomy". Therefore, the autonomy of various unmanned systems and platforms will have to be improved with the needs of the battlefield in the future. The unmanned swarm combat system will have higher perception, analysis, planning, decision-making and execution capabilities, and must be able to continuously complete the necessary control functions under uncertain object and environmental conditions and without participation. The regional distribution, intelligent autonomy and decentralization of an unmanned swarm operation system require orderly collaboration of the UAVs in the unmanned swarm based on the information network, thereby ensuring good battlefield survivability and mission completion capabilities.

An intelligent single unmanned platform interacting with other platforms needs to calculate and evaluate its energy, loss and cost to maximize its "payoff". The competition between individuals inherent in this process causes the individual "payoff" to deviate from the optimal total "utility" of the swarm. Hence, maintaining an individual payoff that is consistent with swarm utility is a key issue in designing a coordination mechanism.

A well-designed coordination mechanism is key to resolving the conflict between the individual payoff and total swarm utility. Further analysis of the competition and conflict between components (individuals) and the system (collective) needs to be performed within the framework of classic multi agent system (MAS) theory [38], complex adaptive systems (CAS) theory [39] and the complex network [40].

Unlike traditional optimization, swarm collaboration does not necessarily improve the adaptability of all individuals by simply selecting a specific behaviour. A complex situation is frequently created when the direct influence of interacting individuals on each other creates a conflict between individuals' pursuits of improving their interests. Game theory provides an effective research framework within which to study interaction and coordination among multiple individuals in a swarm.

All the individuals are participants in the game, and all the optional behaviours form the strategy set of the game. The participants, the strategy set and the payoffs corresponding to various strategies constitute the game. Individuals choose a strategy by evaluating the influences of the surrounding individuals and environmental factors and use adaptive learning from repeated games to maximize their own payoffs and those of the swarm [41,42]. Finally, the swarm coordination mechanism can be determined using Nash equilibrium for the classical game or the evolutionary stable strategy (ESS) for the evolutionary game.

3. Mathematical model

The evolutionary game theory combines "equilibrium" in economics with "adaptability" in biology to depict the process that individuals adapt to the external environment through learning, imitation and trial-and-error under boundary rationality and asymmetric information. And the PGG provides a basic theoretical framework for revealing the cooperative evolution mechanism and coping with the tragedy of the commons. PGG reflects that investors(collaborators) and hitchhikers (non-collaborators) play strategic games over time based on cost, multiplication factor, selection intensity, etc., which makes the proportion of collaborators and betrayers in the population change dynamically, and finally tends to an evolutionarily stable state. The research focus of PGG is to calculate the mathematical expectation of the proportion of collaborators in a population after multi-round game, that is, the average abundance, and then analyze the relationship between average abundance and parameters (i.e., cost, multiplication factor, selection intensity, etc.) to achieve the ultimate purpose of manual control.

In essence, the autonomous collaboration of unmanned swarms is a game process of multi-party and multi-round, which focuses on the autonomous allocation of public resources. Therefore, we use multi-player public goods evolutionary game to model the cooperative evolution of unmanned swarms. The mapping between the concepts of cooperative evolution in unmanned swarms and multi-player public goods evolutionary game is listed in Table 1.

Table 1 Relationship between the concepts of the unmanned swarm and the multiplayer public goods game

Autonomous collaboration of unmanned swarm	Multi-player public goods evolutionary game
Unmanned swarm	Mixed homogeneous population
Public resources required by autonomous collaboration (ammunition, communication, etc.)	Public goods

Continued

Autonomous collaboration of unmanned swarm	Multi-player public goods evolutionary game
Multiple unmanned platforms involving in autonomous collaboration	Multi-player
Individual unmanned platforms	Individuals
Individual unmanned platforms as research objects	Focal individual
Cooperative behavior where platforms are willing to contribute resources to the swarm	Strategy A
Non-cooperative behavior where platforms prefer "free-riding" rather than contributing resources to the swarm	Strategy B
Public resources the swarm gives back to platforms under different strategies	Pay-off
Payoff-based strategy transition between unmanned platforms	Game
Dynamic variations in the proportion of platforms that take different strategies in multiple rounds of game	Evolutionary
After multiple rounds, the game is terminated after the proportion of platforms stabilizes	Evolutionary stable state
Expected proportion of cooperators (non-cooperators) in the swarm in the evolutionary stable state	Average abundance
Average abundance of cooperators in the swarm is larger than 0.5	Strategy A dominates

3.1 Multiplayer evolutionary game model

A well-mixed swarm with a population size N is assumed. Each individual makes choices and performs updates within a finite strategy set $\{A,\ B\}$. An iterative process (evolution process) is used to adjust the ratio of the number of A/B-type individuals in the population to N in real time. This ratio ultimately converges to a well-defined value, corresponding to a stable evolutionary state.

The multiplayer evolutionary game consists of the following three steps.

(i) An individual X (type A or type B) is randomly selected from N individuals in the swarm. Then, $d-1$ individuals are chosen from the remaining $N-1$ individuals. The selected $d(d<N)$ individuals form a group. If the number of A-type individuals in the group is $k(0\leqslant k\leqslant d-1)$, then the number of B-type individuals is $d-k-1$.

(ii) Games are played between the focal individual X and the remaining $d-1$ individuals in the group. Each party chooses game strategies from $\{A,\ B\}$. The payoff of X is a_k if an A-type strategy is chosen and b_k if a B-type strategy is chosen.

(iii) After each round of the game, the focal individual X evaluates its payoff generated by each strategy. The strategy is updated based on the imitation dynamics or the aspiration-driven rule.

These three steps are repeated until a stable evolutionary state is reached. The types of the d individuals in the group are randomly selected. Therefore, the probability of the focal individual X encountering k A-type individuals and $d-k-1$ B-type individuals during games between itself and the $d-1$ individuals satisfies the mathematical constraint of a hypergeometric distribution [43]. For example, the probability of an A-type focal individual X encountering k A-type individuals and $d-k-1$ B-type individuals is $P_A(N,i;\ d,k)=C_{i-1}^{k}C_{N-i}^{d-k-1}\Big/C_{N-1}^{d-1}$, where i is the number of A-type individuals among the N individuals in the population; C_{i-1}^{k} and C_{N-i}^{d-k-1} are the numbers of combinations of individuals choosing the A- and B-type strategies, respectively; and C_{N-1}^{d-1} is the number of combinations of individuals participating in the selection. The probability $P_A(N,i;\ d,k)$ corresponds to the payoff a_k. One A-type focal individual X could be faced with d possible encounters and obtain d possible payoffs during one round of the game. Thus, the expected payoff of an A-type focal individual X during a given round of game is

$$\pi_A(i)=\sum_{k=0}^{d-1}\frac{C_{i-1}^{k}C_{N-i}^{d-k-1}}{C_{N-1}^{d-1}}a_k. \tag{1}$$

Similarly, $P_B(N,i;\ d,k)=C_{i}^{k}C_{N-i-1}^{d-k-1}\Big/C_{N-1}^{d-1}$. The expected payoff for a B-type focal individual X in a given round of the game is

$$\pi_B(i)=\sum_{k=0}^{d-1}\frac{C_{i}^{k}C_{N-i-1}^{d-k-1}}{C_{N-1}^{d-1}}b_k. \tag{2}$$

The aforementioned results were derived in our previous study [30–32].

3.2 Aspiration-driven dynamics

The strategy updating mechanism can be generally divided within the framework of evolutionary game theory into two categories: imitation dynamics [21] and aspiration-driven dynamics [44–46]. The results of previous studies suggest that aspiration-driven dynamics can improve the average abundance and thus boost collaboration more effectively than traditional imitation dynamics for both the prisoner's dilemma game and PGGs [47,48]. Based on aspiration-driven dynamics, the probability of the focal individual updating from the A-type to the B-type is

$$P_{A\to B} = \frac{1}{1+\mathrm{e}^{\omega(\pi_A(i)-\alpha)}} \tag{3}$$

where α represents the aspiration of individual X; ω is a coefficient used to adjust the determination level of the term $\pi_A-\alpha$ for $P_{A\to B}$. If $\pi_A-\alpha=0$ ($P_{A\to B}=1/2$), i is equally inclined towards both strategies. If $\pi_A-\alpha>0$ (the payoff of i exceeds the aspiration and $P_{A\to B}<1/2$), i is inclined towards the A-type strategy. If $\pi_A-\alpha<0$ (the payoff of i is lower than the aspiration and $P_{A\to B}>1/2$), i is inclined towards the B-type strategy.

Similarly, the probability of the focal individual updating from the B- to the A-type strategy is

$$P_{B\to A} = \frac{1}{1+\mathrm{e}^{\omega(\pi_B(i)-\alpha)}}. \tag{4}$$

In any strategy updating mechanism, the number of A-type individuals in every round of the evolutionary game changes in one of the following three ways: decreasing by 1, $i\to i-1$; increasing by 1, $i\to i+1$; and remaining unchanged, $i\to i$.

Equations (3) and (4) can be used to determine the corresponding transition probability as follows:

$$P(i\to i-1) = T_i^- = \frac{i}{N}\frac{1}{1+\mathrm{e}^{\omega(\pi_A(i)-\alpha)}}, \tag{5}$$

$$P(i\to i+1) = T_i^+ = \frac{N-i}{N}\frac{1}{1+\mathrm{e}^{\omega(\pi_B(i)-\alpha)}}, \tag{6}$$

$$P(i\to i) = 1-T_i^- - T_i^+. \tag{7}$$

4. Strategy dominance rules

In this section, the average abundance is first defined, and then a mathematical expression for the average abundance is obtained. The rules for collaborative strategy dominance are derived by expanding the average abundance function in a first-order Taylor series.

4.1 Average abundance

Definition 1 Average abundance. Consider that the number of A-type combat units in the swarm is j, where the proportion j/N is a random variable. Let $\nu(j)$ denote the probability distribution of j/N. Then, the expected value of j/N is defined as the average abundance of A-type combat units in the swarm.

This definition can be used to express the average abundance ($\langle X_A(j)\rangle$) of the collaborative strategy A as

$$\langle X_A(j)\rangle = \sum_{j=0}^{N}\frac{j}{N}\nu(j). \tag{8}$$

The average abundance is calculated by determining $\nu(j)$ of the random variable. $\nu(j)$ is the stationary distribution (φ_j ($j\in[0, N]$)) of a Markov chain with nonabsorbing states, where φ_j satisfies the detailed balance condition [49,50]:

$$\varphi_j T_j^+ = \varphi_{j+1}T_{j+1}^-. \tag{9}$$

The following equation can be derived from (9):

$$\varphi_j = \frac{\prod_{i=0}^{j-1}T_i^+}{\prod_{i=1}^{j}T_i^-}\varphi_0 = \prod_{i=0}^{j-1}h(i)\varphi_0,\quad j\geqslant 1 \tag{10}$$

where $h(i)=\dfrac{T_i^+}{T_{i+1}^-}$. As the stationary distribution φ_j satisfies $\sum_{j=0}^{N}\varphi_j=1$,

$$\sum_{j=0}^{N}\varphi_j = \varphi_0+\sum_{j=1}^{N}\prod_{i=0}^{j-1}h(i)\varphi_0 = 1. \tag{11}$$

Thus,

$$\varphi_0 = \frac{1}{1+\sum_{j=1}^{N}\prod_{i=0}^{j-1}h(i)}.$$

Substituting this result into (10) yields

$$\varphi_j = \frac{\prod_{i=0}^{j-1}h(i)}{1+\sum_{j=1}^{N}\prod_{i=0}^{j-1}h(i)},\quad j\geqslant 1. \tag{12}$$

The average abundance of strategy A is expanded by substituting the equation given above into (8):

$$\langle X_A(j)\rangle = \sum_{j=0}^{N}\frac{j}{N}\varphi_j = \sum_{j=1}^{N}\frac{j}{N}\frac{\prod_{i=0}^{j-1}h(i)}{1+\sum_{j=1}^{N}\prod_{i=0}^{j-1}h(i)} \tag{13}$$

where

$$h(i) = \frac{T_i^+}{T_{i+1}^-} = \frac{(N-i)(1+\mathrm{e}^{\omega(\pi_A(i+1)-\alpha)})}{(i+1)(1+\mathrm{e}^{\omega(\pi_B(i)-\alpha)})}. \tag{14}$$

4.2 Strategy dominance condition

Definition 2 Strategy dominance. When the game reaches a stable evolutionary state during an unmanned swarm operation, a strategy with an average abundance above 0.5 is considered dominant.

Thus, the collaborative strategy dominance is denoted as

$$\langle X_A(j)\rangle = \sum_{j=0}^{N}\frac{j}{N}\varphi_j > \frac{1}{2}. \tag{15}$$

The equation given above can be expanded in a first-order Taylor series as follows:

$$\varphi_j \approx \varphi_j(\omega)|_{\omega=0} + \omega\left[\frac{\partial}{\partial\omega}\varphi_j\right]_{\omega=0} \tag{16}$$

where

$$\varphi_j(\omega)|_{\omega=0} = \varphi_j(0) = \frac{C_N^j}{2^N}. \tag{17}$$

Substituting the equations presented above into (18) yields

$$\frac{\partial}{\partial\omega}\varphi_j|_{\omega=0} = \frac{C_N^j}{2^{(2N+1)}}2^N\sum_{k=1}^{j}[\pi_A(k)-\pi_B(k-1)]- \frac{C_N^j}{2^{(2N+1)}}\sum_{k=1}^{N}C_N^k\sum_{i=1}^{k}[\pi_A(i)-\pi_B(i-1)]. \tag{18}$$

Substituting (1) and (2) into (18) yields

$$\pi_A(i)-\pi_B(i-1) = \sum_{k=0}^{d-1}\frac{C_{i-1}^k C_{N-i}^{d-1-k}}{C_{N-1}^{d-1}}(a_k-b_k), \tag{19}$$

because

$$\sum_{j=0}^{N}\frac{j}{N}\varphi_j(0) = \sum_{j=0}^{N}\frac{j}{N}\cdot\frac{C_N^j}{2^N} = \frac{1}{2}. \tag{20}$$

The strategy dominance condition is equivalent to

$$\sum_{j=0}^{N}\frac{j}{N}\omega\left[\frac{\partial}{\partial\omega}\varphi_j\right]_{\omega=0} > 0. \tag{21}$$

Substituting (18) and (19) into (21) yields

$$\frac{\omega}{4N(2^N)}\left[\sum_{j=1}^{N}(2j-N)C_N^j\sum_{i-1}^{j}\sum_{k=0}^{d-1}\frac{C_{i-1}^k C_{N-i}^{d-1-k}}{C_{N-1}^{d-1}}(a_k-b_k)\right] > 0. \tag{22}$$

Then,

$$\sum_{i=1}^{N}C_{i-1}^k C_{N-i}^{d-1-k}\sum_{j=1}^{N}(2j-N)C_N^j = 2^{N-d}NC_{N-1}^{d-1}C_{d-1}^k. \tag{23}$$

Combining (18) and (19) yields

$$\frac{\omega}{4(2^d)}\sum_{k=0}^{d-1}[C_{d-1}^k(a_k-b_k)] > 0. \tag{24}$$

In summary, the collaborative strategy dominance condition is

$$\sum_{k=0}^{d-1}[C_{d-1}^k(a_k-b_k)] > 0. \tag{25}$$

Equation (25) is a collaborative strategy dominance condition that applies to any multiplayer strategy game. The strategy dominance conditions of traditional imitation dynamics depend entirely on the sum of the payoff differences among different strategies and $\sum_{k=0}^{d-1}(a_k-b_k) > 0$ [19]. However, the aspiration-driven model adds an extra weight to the payoff differences between strategies, i.e., $\sum_{k=0}^{d-1}[C_{d-1}^k(a_k-b_k)] > 0$. Hence, the number k of collaborative strategy holders becomes particularly important. As a consequence of the symmetry of the number of combinations C_{d-1}^k, C_{d-1}^k has the strongest influence on strategy dominance when k is the median of d(i.e., there are equal numbers of collaborators and noncollaborators in the swarm).

The preceding rigorous mathematical derivation of the strategy dominance condition for a multiplayer evolutionary game lays a theoretical foundation for the analysis of two types of public goods games in the following section.

5. Evolutionary game analysis

On the basis of the average abundance of unmanned swarm obtained in Subsection 4.1, we will analyze the impact of parameter adjustment on it.

The parameters in the model have realistic military significance. Take cost as an example. Cost (such as communication, intelligence, firepower and other resources) is a factor that we must consider when studying swarm cooperation. In real combat, we pursue to exchange the lowest cost investment for the optimal swarm coordination effect, and finally achieve the maximum combat effectiveness. On the contrary, if the cost is too high, we will finally achieve the combat purpose, which is also "the gain outweighs the loss". Another typical parameter is the multiplication factor. The multiplication factor determines the "appreciation rate" of resources. The appreciation of resources is reflected in the overall efficiency of "1 + 1 > 2" brought by swarm coordination. Too small multiplication factor cannot promote the transformation of the unmanned platform to the cooperation strategy, and too large multiplication factor has no practical significance. Studying the influence law of multiplication factor on swarm cooperation level is of great significance for reasonably setting the size of multiplication factor and improving the overall cooperation level of swarm.

The linear and threshold PGGs are analyzed to determine the payoffs, the strategy dominance characteristics are simulated, and reasonable suggestions are proposed for the design of autonomous coordination mechanisms of swarms.

5.1 Characteristic analysis of average abundance

Let $N = 100$, $d = 15$, $c = 1$, $r = 1.3$, $\alpha = 1$, and draw the basic curve (see Fig. 2). Since $X_A < 0.5$, this case is a non-dominant case, that is, most units choose strategy B. Therefore, we try to regulate relevant parameters to increase the average abundance of unmanned swarm and promote cooperation.

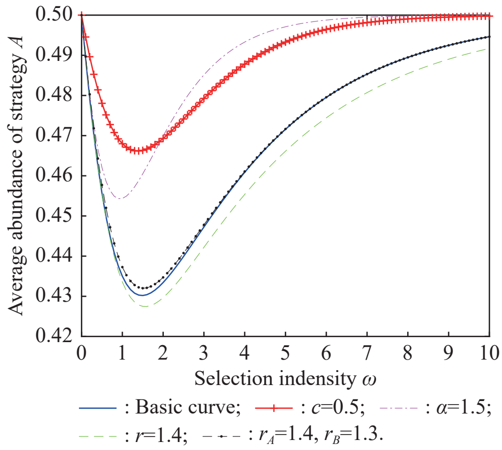


Fig. 2 Effects of different factors on average abundance

As shown in Fig. 2, reducing the cost or increasing the aspiration level can raise the proportion of cooperators. However, increasing the multiplication factor will cause the average abundance curve to deviate downward from the basic curve, which is because increasing pay-off of cooperators and betrayers by the same margin will make the "free riding" situation more serious. Consequently, we try to separate the multiplication factor of cooperators from that of betrayers, only increase the multiplication factor r_A of cooperators (the multiplication factor r_B of betrayers remains unchanged), and find that the average abundance curve deviates upward from the basic curve.

Furthermore, we simulate the average abundance under different r_A (see Fig. 3). When $r_A = 2$, the average abundance is approximately equal to 0.5, which indicates that the proportion of cooperators and betrayers in the swarm is basically balanced. With the further increase of r_A, when $r_A = 2.65$, the average abundance will be greater than 0.5 at $\omega \approx 10$, while when $r_A = 2.9$, the average abundance will be greater than 0.5 at $\omega \approx 5$. Thus, we can reach the following conclusions.

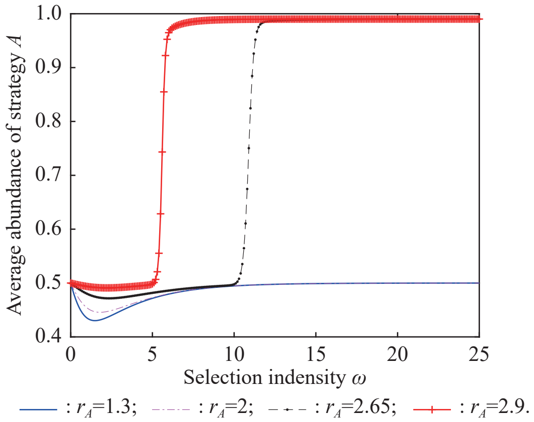


Fig. 3 Effects of different r_A on average abundance

(i) The adjustment on r_A can switch the dominant strategy, making the average abundance of strategy A greater than 0.5;

(ii) The lower the ω is, the more stringent requirement for r_A will be, and the higher the ω is, the looser requirement for r_A will be $X_A(\omega = 5, r_A = 2.9) > 0.5$, while $X_A(\omega = 10, r_A = 2.65) > 0.5$.

In order to investigate the regulation sensitivity of different parameters, we simulate the affecting degree of unit variation of c, α, r_A on the average abundance. We select the simulation results with $\omega = 0$, 5, 15 to be discussed, as shown in Fig. 4(a), Fig. 4(b), and Fig. 4(c), respectively.

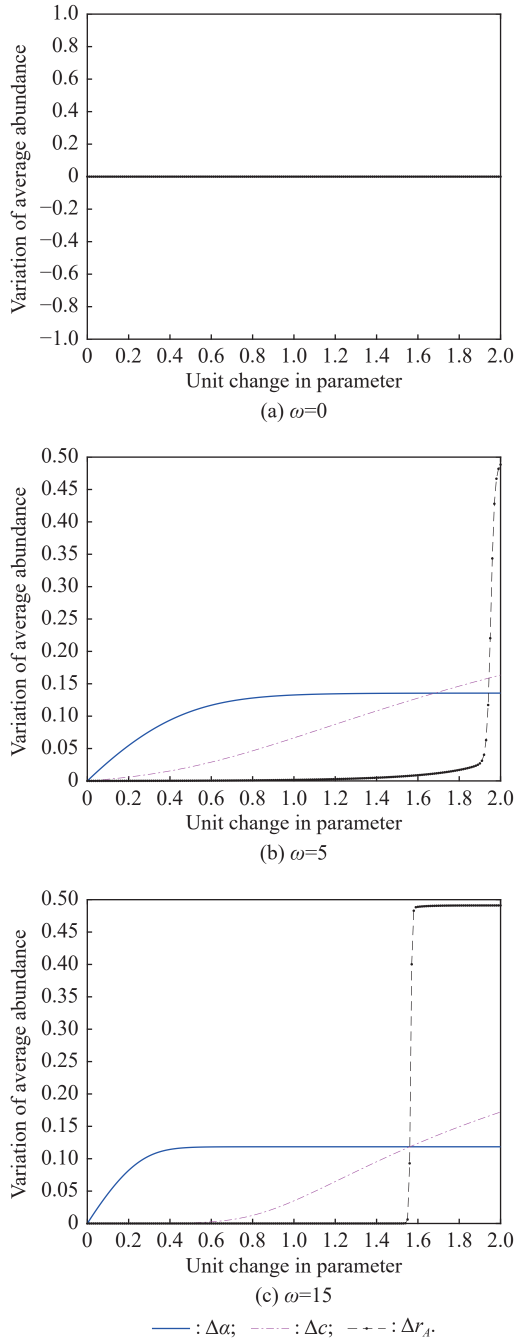


Fig. 4 Effects of unit variation in parameters on average abundance

(i) When $\omega = 0$, the average abundance is identically equal to 0.5, and thus the parameter regulation loses its effect (see Fig. 4(a)).

(ii) When $\omega \neq 0$ and unit variation of parameters (i.e., Δ) is small (note that the threshold of Δ is related to ω: $\Delta \approx 1.70|_{\omega=5}$, $\Delta \approx 1.53|_{\omega=15}$), the change in value of average abundance caused by adjusting α and c is much greater than adjusting r_A (see Fig. 4(b), Fig. 4(c)). The regulation of α and c is more sensitive than that of r_A.

(iii) When $\omega \neq 0$ and Δ is large, the regulation effect of r_A is much better than that of α and c. And the larger ω is, the more sensitive r_A is, i.e., a small Δ_{r_A} leads to a large increase in average abundance: $\Delta < X_A(\omega = 5, \Delta_{r_A} = 1.95) > \approx 0.43$, while $\Delta < X_A(\omega = 20, \Delta_{r_A} = 1.55) > \approx 0.48$ (see Fig. 4(b), Fig. 4(c)).

To improve the average abundance, the ideal measure is to increase the multiplication factor, reduce the cost of cooperators, or both. However, in order to ensure the effectiveness of the operation in the actual battlefield, the cost is difficult to reduce or even increases. Therefore, it is necessary to consider increasing both r_A and c. Fig. 5 shows the change of average abundance when r_A and c increase at the same time (c increases by 50%, r_A increases by 69% and 73%, respectively). Accordingly, as long as r_A increases by more than 73%, not only can the adverse effect of cost increasing on average abundance be offset, but also the cooperation in swarm can be promoted.

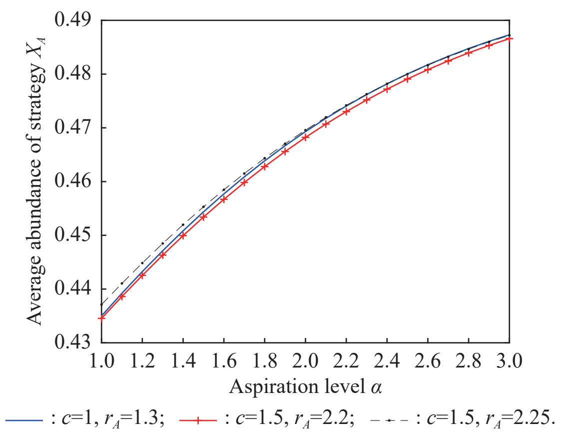


Fig. 5 Effect of increase in cost and multiplication factor on average abundance

Unfortunately, the above regulation can only achieve a limited increase in the average abundance, that is, it cannot make the average abundance greater than 0.5. The conversion of dominant strategies (a large increase in average abundance) depends on a large selection intensity ω and a large unit variation Δ_{r_A}, and thus we further increase r_A under the premise of increasing c by 50% (see Fig. 6). According to the results in Fig. 6, when $r_A = 2.52$ and $\omega \approx 15$, X_A will be greater than 0.5; when $r_A = 2.65$ and $\omega \approx 5$, X_A will be greater than 0.5.

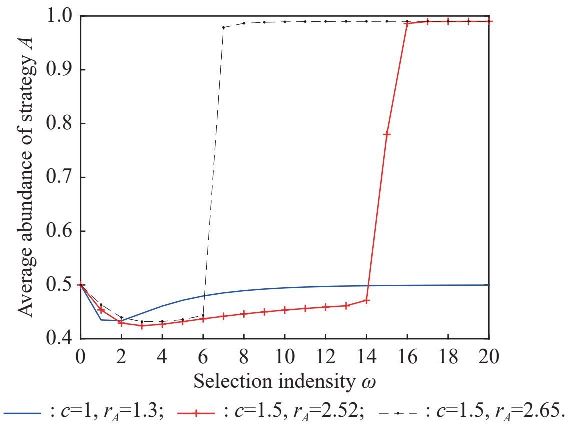


Fig. 6 Stragy alternation by increasing cost and multiplication factor

The increase of r_A means that the hitchhiker will no longer get as much pay-off as the cooperator, and the decrease of pay-off will directly increase the strategy update probability $P_{B\to A}$, so then more units tend to cooperate (more betrayers transfer to cooperators).

According to the above simulation results and conclusions, we can consider the following measures from two dimensions of management and technology in the actual control of unmanned swarm cooperation:

(i) Increase the multiplication factor value r_A of cooperators as much as possible. For example, with the help of advanced management means, for each combat unit in the swarm, its investment (i.e., cost c) in previous operations can be accumulated, and those with higher cumulative investment will be given more supplies (e.g., ammunition) or higher supply priority in the follow-up operations;

(ii) Minimize the cost c for each operation. For example, with the help of advanced technology means, improve the reliability and survivability of combat units or the strike accuracy and damage-power of ammunition.

In addition, since c, r and α are closely related to specific operation tasks, it is also necessary to discuss specific control measures in combination with operation tasks under the limitation of parameter value range.

5.2 Characteristic analysis of linear PGGs

When X chooses collaborative strategy A in the linear PGGs model, the total quantity of resources that the group can acquire is $kc+c$. The total payoff after the cost increase is $r(kc+c)$. Thus, the individual payoff is $r(kc+c)/d$. As the initial investment of X has a value c, the net payoff of X is $[r(kc+c)/d]-c$. If X selects strategy B, the parameters presented above change to kc, rkc, rkc/d and rkc/d. Thus,

$$a_k = \frac{r(kc+c)}{d} - c, \tag{26}$$

$$b_k = \frac{rkc}{d}. \tag{27}$$

The payoff matrix is shown in Table 2.

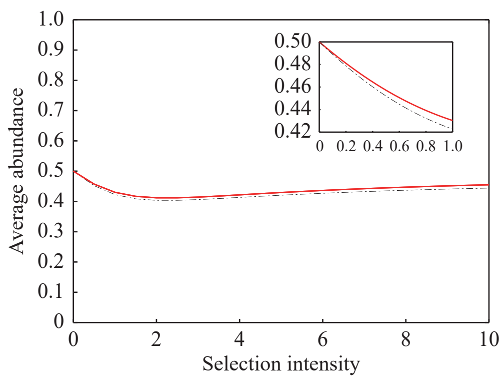
Table 2 Payoff for the linear PPG model

Strategy	Number of cooperators					
	d−1	⋯	k−1	⋯	1	0
A	$rc-c$	⋯	$[r(kc+c)/d]-c$	⋯	$[2rc/d]-c$	$[rc/d]-c$
B	$r(d-1)c/2$	⋯	rkc/d	⋯	rc/d	0

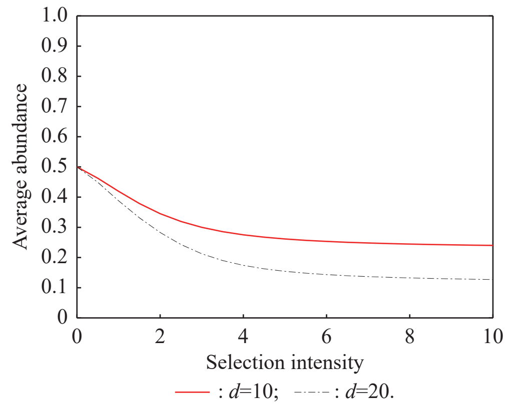
As $a_k-b_k=c(r/d-1)$ and $1<r<d$ are generally assumed, (25) can be used to evaluate the strategy dominance as follows:

$$\sum_{k=0}^{d-1}\left[C_{d-1}^{k}(a_k-b_k)\right]=2^{d-1}c\left(\frac{r}{d}-1\right)<0. \tag{28}$$

Therefore, the linear PGGs model is a non-collaborative dominance game, that is, the non-collaborative strategy rather than the collaborative strategy dominates the swarm when the stable evolutionary state is reached. The dominant characteristics of this game strategy are determined by analyzing the influences of the selection intensity ω, reward coefficient r and aspiration level α on the average abundance X_A in simulations with $\alpha=1$, $N=100$ and $c=1$. The relationship between ω and r and X_A is shown in Fig. 7.



(a) Fixed reward coefficient



(a) $r=d/2$

Fig. 7 Relationship between X_A and selection intensity and reward coefficient for the linear PGGs model

The reward coefficient is fixed in Fig. 7(a) and $d/2$ in Fig. 7(b). In Fig. 7(a), d=10 or 20 and $r=2$. The average abundance X_A = = 0.5 for a selection intensity $\omega=0$. When ω is small (as shown in the top right corner), it is difficult to satisfy the aspiration of the collaborators. Thus, large numbers of collaborators change their strategies, which produces a downturn in X_A. As ω increases, X_A improves slightly and stabilizes at approximately 0.45. In Fig. 7(b), d=10 or 20 and $r=d/2$. Fig. 7(b) shows that increasing r (from 2 to 5 and 10) causes X_A to decrease progressively compared to Fig. 7(a). The larger the increment in r is, the larger the decrement in X_A is, i.e., $X_A(\omega)|_{r=10}<X_A(\omega)|_{r=5}$. One reason for this result is that the simultaneous increase in the payoffs of both the collaborative and non-collaborative units in the swarm aggravates "free-riding" behaviour and causes many combat units to become non-collaborators.

Conclusion 1 Under constants c and α for the linear PGGs model, collaborators have a high X_A for a weak ω ($\omega\to 0$) and a small r. The effect of a weak w on promoting cooperation has been verified in a variety of fields, such as biological genetics, molecular evolution and cultural evolution [51−53], although the action mechanism has not been identified.

Although collaboration is not the dominant strategy in unmanned swarm operations in the linear PGGs model, the influences of ω and r on strategy updating could be mitigated by presetting small values of ω and r, thereby increasing the X_A of the collaborators in the swarm and maximally facilitating swarm collaboration.

Fig. 8 shows the simulated results for the relationship between α and X_A for ω=0, 5, 10, 15 and 20, $c=1$ and $r=1.1$.

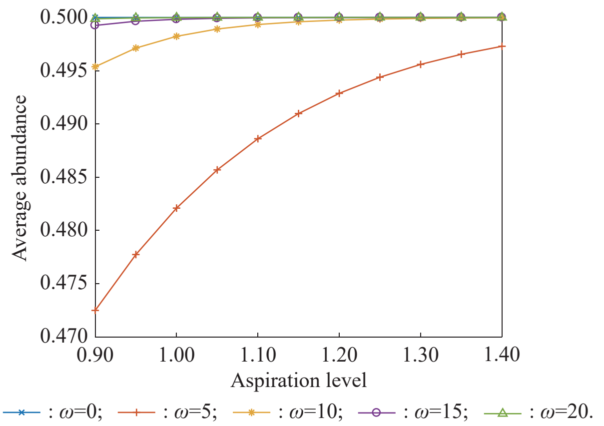


Fig. 8 Relationship between the average abundance and aspiration level

In Fig. 8, X_A increases with α, indicating that increasing α makes it even more difficult to attain the expected non-collaborative payoff. Equation (4) shows that the strategy updating probability $P_{B\to A}$ increases and more non-collaborators become collaborators. At a sufficiently high α, $\lim_{\alpha\to\infty}X_A = 1/2$ at any ω.

Conclusion 2 Under a constant c and r for the linear PGGs model, the collaborators have a high X_A for high α.

Therefore, the probability that non-collaborators will choose the collaborative strategy (that is, switch from the non-collaborative strategy) could be increased by presetting a large α in unmanned swarm operations in the linear PGGs model, thereby improving the average abundance of collaborators in the swarm and maximally facilitating swarm collaboration.

5.3 Characteristic analysis of threshold PGGs

Within the threshold PGGs model, individuals only earn payoffs when the total number of collaborative strategy holders in the group is not smaller than a threshold m. When $k \geqslant m$ and X chooses collaborative strategy A, the total quantity of resources that the group can acquire is $kc+c$. The total payoff after the cost increase is $r(kc+c)$. Thus, the individual payoff is $r(kc+c)/d$. If X selects strategy B, the parameters presented above change to kc, rkc, rkc/d and $rkc/d+c$. Thus,

$$a_k = r(kc+c)/d, \tag{29}$$

$$b_k = [rkc/d]+c. \tag{30}$$

The payoff matrix is presented in Table 3.

Table 3 Payoff for the threshold PPG model

Strategy	Number of cooperators						
	$d-1$	$\cdots$	k	$\cdots$	$m-1$	$\cdots$	0
A	rc	$\cdots$	$[r(kc+c)/d]-c$	$\cdots$	mrc/d	$\cdots$	0
B	$[r(d-1)c/d]+c$	$\cdots$	$[rkc/d]+c$	$\cdots$	0	$\cdots$	0

Thus,

$$\sum_{k=0}^{d-1}\left[C_{d-1}^{k}(a_k-b_k)\right] = \sum_{k=m}^{d-1}C_{d-1}^{k}\left(\frac{rc}{d}-c\right)+C_{d-1}^{m-1}\frac{mrc}{d}. \tag{31}$$

Unlike for linear PGGs, the equation presented above does not exhibit any notable characteristics of strategy dominance. The severity of the two types of strategy dominance conditions, i.e., aspiration-driven dynamics and imitation dynamics, is compared in the following section.

Let $\sum_{k=0}^{d-1}\left[C_{d-1}^{k}(a_k-b_k)\right]>0$, and substitute (28) into this equation yields the strategy dominance condition:

$$r > \frac{d\sum_{k=m}^{d-1}C_{d-1}^{k}}{\sum_{k=m}^{d-1}C_{d-1}^{k}+mC_{d-1}^{m-1}}. \tag{32}$$

Setting $t = d\sum_{k=m}^{d-1}C_{d-1}^{k}\bigg/\left(\sum_{k=m}^{d-1}C_{d-1}^{k}+mC_{d-1}^{m-1}\right)$ yields the following equation:

$$t = \frac{d\left(\sum_{k=m}^{d-1}C_{d-1}^{k}+mC_{d-1}^{m-1}\right)-dmC_{d-1}^{m-1}}{\sum_{k=m}^{d-1}C_{d-1}^{k}+mC_{d-1}^{m-1}} = d-m\frac{(d-m)C_{d-1}^{m-1}+mC_{d-1}^{m-1}}{\sum_{k=m}^{d-1}C_{d-1}^{k}+mC_{d-1}^{m-1}}.$$

Equation (32) is equivalent to

$$r > d-m\frac{(d-m)C_{d-1}^{m-1}+mC_{d-1}^{m-1}}{\sum_{k=m}^{d-1}C_{d-1}^{k}+mC_{d-1}^{m-1}}. \tag{33}$$

The strategy dominance condition under imitation dynamics is $\sum_{k=0}^{d-1}(a_k-b_k)>0$. Equation (33) is derived by using (29) and (30):

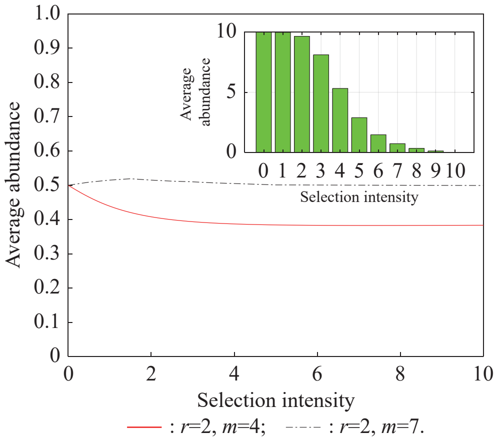
$$r > d-m. \tag{34}$$

The following observations are made by comparing (32) and (33).

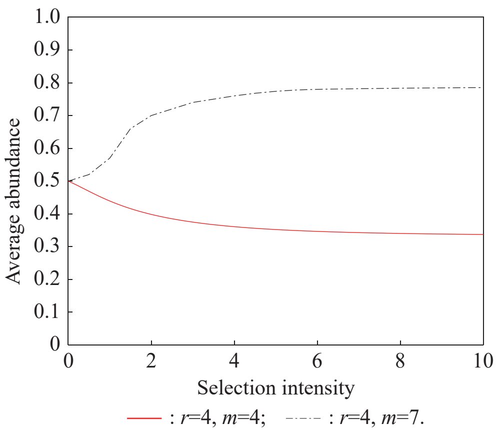
(i) For large m, the property of combinatorial numbers results in $(d-m)C_{d-1}^{m-1} > \sum_{k=m}^{d-1}C_{d-1}^{k}$ in (33). Therefore, it is easier to satisfy (33) than (34). That is, the dominance condition for the aspiration-driven strategy is easier to fulfil than that for the imitation dynamics strategy, indicating that collaborative strategy dominance requires a lower payoff (i.e., a smaller r) under the aspiration-driven rules.

(ii) Conversely, $(d-m)C_{d-1}^{m-1} < \sum_{k=m}^{d-1} C_{d-1}^{k}$ in (31) for small m. Therefore, it is easier to satisfy (34) than (33). The dominance condition of the aspiration-driven strategy is stricter than that of the imitation dynamics strategy. The dominance condition for the imitation dynamics strategy can facilitate intra-swarm collaboration more effectively than that of the aspiration-driven strategy.

The characteristics of the aspiration-driven strategy dominance for the threshold PGGs model are analyzed by determining the influences of different m and r on collaborative strategy dominance for simulations with $\alpha = 1$, $N = 100$, $c = 1$, and $d = 10$. The effects of m and r on X_A are shown in Fig. 9.



(a) Influence of the threshold on X_A



(b) Influence of the threshold on X_A for a fixed reward coefficient

Fig. 9 Effect of the threshold and reward coefficient on X_A within the threshold PPG model

Fig. 9 (a) shows the influence of the threshold on X_A, and Fig. 9(b) shows the influence of the threshold on X_A for a fixed reward coefficient. In Fig. 9(a), when $r = 2$ and m increases from 4 to 7, X_A of the collaborative strategy increases, and the dominant strategy is also changed ($X_A|_{m=4} < 0.5$ changes to $X_A|_{m=7} > 0.5$; the dominant strategy is switched from B to A). The top right corner of Fig. 9(a) shows the relationship between several m and r values. As m increases, the required r (i.e., the required payoff) becomes increasingly smaller when the collaborative strategy is dominant. Unlike the results shown in Fig. 9(a), Fig. 9(b) shows that although m is still 4 or 7, $X_A\big|_{m=4,\, r=4} > X_A\big|_{m=4,\, r=2}$ and $X_A\big|_{m=7,\, r=4} > X_A\big|_{m=7,\, r=2}$ at the same ω and m, because r increases from 2 to 4.

Conclusion 3 Under a constant c and α for the threshold PGGs model, a large m promotes collaboration, even at small r. For fixed m, a large r promotes collaboration.

Thus, simultaneously increasing m and r can exploit the advantage offered by aspiration in promoting swarm collaboration and realize collaborative strategy dominance in unmanned swarm operations within the threshold PGGs model.

For the management of actual unmanned swarms, an autonomous collaborative rule could be preset based on the evolutionary game model and aspiration-driven dynamics developed in Section 2. Additionally, according to each specific combat scenario, $(r_1 - r_3)$ could be changed by adjusting the parameters, such as c, α, r and m. However, the rule for changing $(r_1 - r_3)$ should be preset based on Conclusions 1−3. When communication with the ground control station is interrupted, the unmanned swam can respond effectively following the preset rules and realize collaboration strategy dominance, thereby seamlessly completing the military mission.

For example, α is usually fixed for UAVs in actual operation. Moreover, it is difficult to further compress operational costs c, such as ammunition and communication. In this case, the unmanned swarms may automatically set a high m and a large r for the collaborative process based on r_3 within the framework of R_C to enhance the proportion of collaborators in the swarm in the stable evolutionary state and facilitate collaborative behaviour and collaborative strategy dominance.

6. Conclusions

Autonomous collaboration of unmanned swarms is the focus of military research on “new combat capabilities” and “disruptive technologies”. A key problem in autonomous collaboration is the design of a reasonable mechanism to increase the proportion of collaborators in a combat swarm, thus ensuring the overall combat effectiveness of the swarm. An aspiration-driven multiplayer evolutionary game model is built in this study. Mathematical derivations are used to obtain the average abundance function of the model, the strategy dominance conditions and the linear and threshold PGGs. The simulation results show that increasing the multiplication factor r_A and reducing the cost c can improve the average abundance of cooperators, furthermore, when the unit variation Δ is large, r_A not only has a high regulation sensitivity, but also can realize the switching of the dominant strategy. The influences of ω, r, α and m on strategy dominance of the two game models are analyzed. Finally, we suggest some proposals to support decision-making for designing the mechanism of unmanned swarm operations.

In this study, the swarm structure is assumed to be well-mixed, and the influence of the structure on the strategy dominance characteristics is not considered. On a real battlefield, a combat platform uses physical/information links to create a network structure. Allen, Lippner and Nowak [54] and Tkadlec et al. [55] have carried out insightful studies on spatial evolutionary games. In a subsequent study, we will use complex networks to calculate the evolutionary game and strategy dominance characteristics of unmanned swarms with specific network structures.

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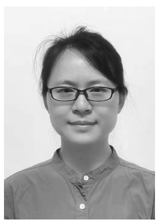
Biographies



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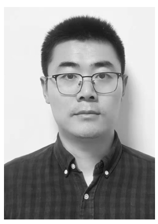

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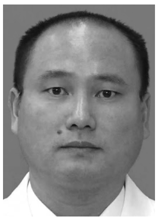

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