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A Strategy Adaptive Evolution Approach Based on the Public Goods Game

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Abstract: Cluster behavior is prevalent in nature. Many individuals change their behavior to adapt to a dynamically changing environment by following simple rules of behavior and interacting with information from neighboring individuals. In this study, the traditional public goods game model is improved by combining the advantages of game theory and interactive learning. A strategy adaptive evolution method based on a public goods game is proposed. The emergence of cooperative behavior in weighted networks under the co-evolution of game strategies and node weights is explored in conjunction with multi-agent interactive learning. The results show that in a public goods game with strategic adaptation, a person's influence becomes greater if their level of adaptation exceeds the desired level, and less otherwise. This weight adjustment is defined by the intensity parameter δ. A moderate δ value can effectively facilitate the occurrence of cooperative evolution. The level of cooperation depends mainly on the weight distribution of participants, which leads to the formation of cooperative clusters controlled by high-weighted cooperators. Even with the great temptation to defect, these cooperators can prevail over defectors. The adjustment of node weights increases the heterogeneity of individuals. This research provides a viable pathway to solve social dilemmas and will further promote the application of multi-agent intelligent decision making.

Keywords: public goods game; strategy adaptation; node weights; cooperative evolution

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1. Introduction

Biological systems are full of amazing diversity and complexity. Coordinated cluster behavior can be generated among individuals based on simple rules of local interaction. For example, in groups composed of large numbers of individuals such as starlings, bacterial communities, ant colonies, and locusts, group division of labor and cooperation can be observed despite the vast differences in scale and cognitive abilities of these systems [1–3]. Cooperation is the basis for the evolution of all types of biological, social, and complex network systems [4,5]. Therefore, it is important to focus on the interaction and strategic transmission between individuals in the cluster. When looking at the evolution of cooperation and defection in structural clusters from a network dynamics perspective, each node is either a cooperator or a defector. Cooperation or betrayal strategies are propagated from one node to another. The research in this field is focused on the proportion and distribution of the number of nodes in different states [6,7]. Accordingly, scholars have tried to understand the evolution of cooperation in terms of social connections, such as the migration of individuals [8], dynamic networks [9,10], and temporal networks [11]. In real interaction scenarios, such as narrow altruism [12], preference for fairness [13,14], individual emotions [15,16], disease transmission dynamics [17] and biological systems [18], numerous examples demonstrate individuals adaptively adjusting their strategies based on the reactions of their opponents. This diversity of strategic adjustments depicts important characteristics of many life systems.

Through the tradition of statistical physics and successful examples, models usually assume that the characteristics of individuals are identical. However, the individual characteristics and social relationships of group members may vary dramatically in nature. The current models may not address the wider ecological and evolutionary issues [19,20]. Many scholars have recently begun to emphasize the role of individual differences. Delgado et al. [21] suggested how individual heterogeneity affects the collective properties of clusters; Farine et al. [22,23] proposed that individual differences in local interaction rules can change cluster behavior. Social relationships specific to many animal groups are particularly likely to influence collective dynamics. This is because individuals of many species, including many birds, mammals, and humans, have often been observed to maintain close relationships and move together with people with whom they have strong social relationships. Helbing et al. [24] proposed that moderate greed can facilitate cooperative evolution and contribute to social cohesion, and further showed that the degree of greediness in cooperative implementation is evolutionarily selected. Li et al. [25] proposed a novel game model with heterogeneously stochastic interaction. The research further clarified the positive role of heterogeneity in the evolution of cooperation. Collective movement models in conjunction with social network structures suggest that social relationships can change individuals' spatial positions in the cluster, as well as the cohesion [26,27] and polarization of the cluster [28]. Empirical data on the effects of social relationships on interaction rules and collective behavior are still very limited. Few studies have examined how social relations within groups affect cluster movements. However, in order to better describe the objective reality, it is necessary to investigate the evolutionary game based on individual attributes. Link weights have attracted considerable attention [29]. In recent years, scholars have conducted numerous studies on the effect of changes in different personal characteristics on the evolution of cooperation. Building on previous work, the impact of players' weights on cooperation in games has been discussed. This seems to be consistent with the fact that each individual may exhibit heterogeneity in terms of social position or social influence in the cluster. In addition, the player weights may change adaptively over time as the player evolves. In the real world, players with greater social influence have a greater degree of adaptation than those with less social influence.

Therefore, this paper focuses on linking the weights of the nodes to the expectations. Adaptive evolution of strategies based on public goods games is proposed, where node weights are used to model the player's role or influence. The choices of individuals in the game process tend to have a large impact on the evolution, while individual choices are often determined by the attributes of individuals under the current model. In real life, some individuals' behavioral choices may not be based on comparisons with individuals around them, but rather on whether they meet their own expectations. Individual expectations are only satisfied and unsatisfied, which leads to nonlinear changes in the cooperation rate in the evolutionary game based on individual expectations. In fact, an individual's expectations can change in response to changes in the surrounding environment or personal decisions. Therefore, each individual has a different role or influence. With dynamic migration simulation, individual interactions are performed according to evolutionary game theory. The payoffs of the game are treated as degrees of adaptation. At each discrete evolutionary time step, individuals are updated randomly. We find that individuals with high fitness have a higher chance of being imitated by others, even if initially all players have the same social influence. The co-evolutionary setting makes the players' social influence gradually heterogeneous in terms of social influence, which in turn promotes cooperation. Additionally, it provides a feasible path for intelligent decision making and collaborative cooperation of multiple agents.

In this paper, a strategy adaptive evolution method based on a public goods game is designed to realize a multi-agent intelligent game and evolution. The rest of this paper is arranged as follows: Section 2 presents the fundamentals of modeling the evolutionary cooperative environment with a public goods game as an individual-to-individual interaction and introducing a node-weighted strategy change mechanism. Sections 3–5 illustrate the effects of expectations and weights on multi-agent cooperative evolution, the outbreak of cooperation in a spatial game, and the effect of population density on cooperative evolution, respectively. Simulation results and performance analysis for the proposed strategies are also presented. Finally, the contents of this paper are summarized and discussed in Section 6.

2. Related Work

This section introduces the modeling environment based on a public goods game and a multi-agent strategy update mechanism.

2.1. Evolutionary Models of Public Goods Games

In this paper, the public goods game is used as a way of interaction between individuals. In a cluster of size N, each individual chooses a strategy at each time step. The strategy is either defection or cooperation. If the individual chooses the cooperative strategy, then it will contribute one point of investment in the public goods game. If the defection strategy is chosen, then the individual will not pay for the investment. When all individuals choose to become defectors or cooperators, the total investment in the public goods game will be multiplied by a gain factor ($r \geq 1$). Finally, the total investment in the public goods game will be evenly distributed to each individual in the population (including defectors and cooperators).

Each individual plays a public goods game with all of its neighbors and accumulates the payoffs. The payoff for an individual i playing a game is

$$P_i^{\Omega} = r\frac{\sum_{j\in\Omega} s_j a}{n} - s_i a = r\frac{n_C^{\Omega} a}{n} - s_i a, \quad (1)$$

where n_c^{Ω} is the number of cooperators in the neighborhood, and the contribution value of a cooperator is a. Usually, it takes the value of one. At a given point in time, the individual's strategy is represented as $s_i(t)$. The cooperative strategy is denoted when $s_i(t)$ is equal to one. The cooperative strategy is denoted when $s_i(t)$ is equal to zero.

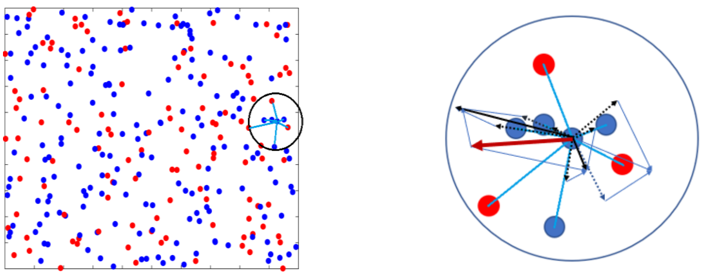
The net payoff to individual i is the sum of the payoffs to all the group games in which it participates. The following equation shows

$$P_i = \sum P_i^{\Omega} \quad (2)$$

The position of an individual is denoted by $x(t)$. The collection of neighbors of an individual i is defined as

$$\Omega_i(t) = \{j \,||x_j(t) - x_i(t)| < R, i \neq j\}, \quad (3)$$

where R is the spatial distance. Figure 1a presents a schematic diagram of the neighbors of an individual in the plane. The black circles are the range of neighbors determined by the central individual and the radius of interaction R.



(**a**) (**b**)

Figure 1. (**a**) Schematic diagram of node neighbors on the two-dimensional plane; (**b**) schematic diagram of the migration direction.

In Figure 1, the red circles represent defectors and the blue circles represent cooperators. The red arrow represents the direction of movement of the central individual.

Usually, each individual has a velocity vector and a position vector, which contain the current velocity and position information of the individual, respectively. The gaming and movement of each individual are performed simultaneously. The individual will update its position according to Equation (4):

$$\vec{x}_i(t+1) = \vec{x}_i(t) + \vec{V}_i(t)\Delta t, \tag{4}$$

where $\vec{V}_i(t)$ represents the velocity vector of i individuals at time step t; $\vec{x}_i(t)$ represents the displacement of individual i, which consists of the migration rate $\vec{V}_i(t)$ and migration direction $\theta_i(t)$; Δt represents the time interval.

In a population, individuals not only update their own strategies according to their neighbors' strategies but are also influenced by the migration direction of their surrounding neighbors. In pursuit of a favorable environment, individuals will follow the migration direction of cooperators and move away from that of defectors. Therefore, we improve the averaging rule for the direction of movement in the Vicsek model. The direction of movement of each individual will be determined by the individual's own strategy. The direction of velocity of each individual can be obtained from Equation (5):

$$\theta_i(t+1) = \arctan\frac{\sum\limits_{j\in\Omega_i(t)} \sin(\theta_{j\to i}(t) + s_j \times \pi)}{\sum\limits_{j\in\Omega_i(t)} \cos(\theta_{j\to i}(t) + s_j \times \pi)}, \tag{5}$$

$$s_j = \begin{cases} 1 & \text{j is a cooperator} \\ 0 & \text{j is a defector} \end{cases}, \tag{6}$$

where $\theta_{j\to i}(t)$ denotes the vector angle of individual j pointing to individual i, and s_j denotes the strategy of individual j. As shown in Figure 1b, the direction pointed by the red arrow is the direction of movement of the central individual.

In the model, if the individual has no neighbors at this time step, then a random direction migration will be performed. The migration direction is chosen randomly from a range of $(0, 2\pi)$. After the migration is completed, each individual updates its set of neighbors again according to the interaction radius R with Equation (3). In a population with migration, the collection of neighbors of an individual may change at each time step.

2.2. Strategy Update Mechanism

The most important aspect of a complete evolutionary step is the strategy update mechanism. When performing a strategy update, an individual can choose to change the current strategy, or change the current position. Whether an individual's adaptation meets the individual's expected standard value is called satisfaction $u_i(t)$.

$$u_i(t) = F_i(t) - Aa_i(t) + \eta_i(t), \tag{7}$$

where $Aa_i(t)$ represents the expectation of the individual, A is the expectation intensity, and $\eta_i(t)$ is the noise.

The expected payoff is updated by the greedy criterion as follows:

$$a_i(t) = \alpha P_{i\max}(t) + (1-\alpha)P_{i\min}(t), \tag{8}$$

where $\pi_{i\max}(t)$ and $\pi_{i\min}(t)$ denote the maximum and minimum payoffs obtained during the whole game, and α denotes the degree of greediness of the individual between zero and one. The maximum and minimum gains of an individual are expressed as a degree of memory for time dependence. They can be calculated according to the following equations:

$$P_{i\max}(t+1) = \begin{cases} P_i(t) & P_i(t) > P_{i\max}(t) \\ P_{i\max}(t) + \mu(P_i(t) - P_{i\max}(t)) & P_i(t) \le P_{i\max}(t) \end{cases}, \tag{9}$$

$$P_{i\min}(t+1) = \begin{cases} P_i(t) & P_i(t) < P_{i\min}(t) \\ P_{i\min}(t) + \mu(P_i(t) - P_{i\min}(t)) & P_i(t) \ge P_{i\min}(t) \end{cases}. \tag{10}$$

The introduction of the parameter $\mu(0 < \mu < 1)$ indicates the time decay scale of the maximum and minimum gains achieved in the past.

If there is no mechanism to contain defectors in the game, the benefits of the cooperators will be damaged by the defectors' free-riding behavior. The population will soon be trapped in the tragedy of the commons. In this study, node weights indicating the social influence of participants in the model are introduced. At the beginning, the same social influence ($w_i = 1$) is assigned to each individual. In subsequent steps, these social influence weights change adaptively according to the interactions. At each time step, each player i gains its cumulative payoff P_i by gaming with its neighbors. The player's fitness is evaluated according to the following expression:

$$F_i(t) = w_i \times P_i(t). \tag{11}$$

In Equation (11), w_i is the individual social influence weight, which is updated with the expectation rule.

$$\begin{cases} w_i = w_i + \delta & P_i(t) > a_i(t) \\ w_i = w_i & P_i(t) = a_i(t), \\ w_i = w_i - \delta & P_i(t) < a_i(t) \end{cases} \tag{12}$$

where δ is the weight intensity. If the payoff is greater than the expected value, the weight will increase. The social influence of the individual will also increase.

The parameter p is introduced to describe the adjustment role in the adaptive strategy. As shown in Figure 2, the process of adaptive strategy state transition is illustrated.

1. Satisfaction ($u_i(t) > 0$): individuals do not change their current strategy and do not migrate;
2. Dissatisfaction ($u_i(t) \le 0$): individuals change their current strategy with probability p and do not migrate, or do not change their strategy with probability $1 - p$ and migrate in the direction of Equation (4).

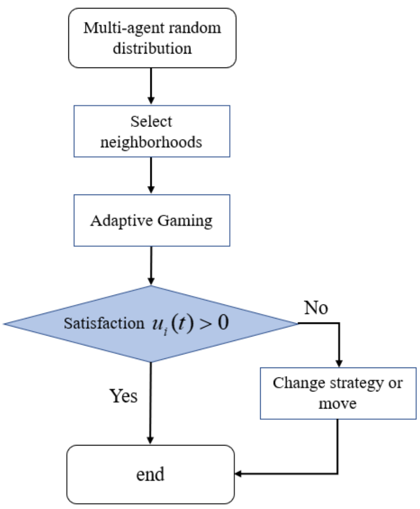


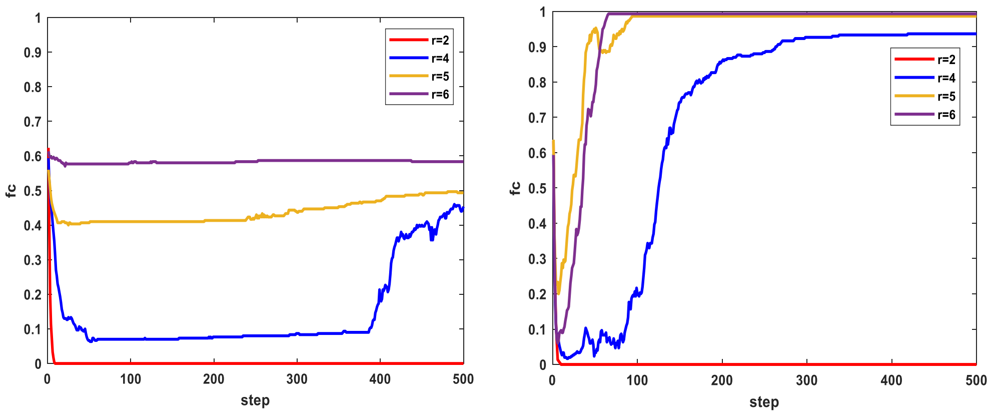
Figure 2. Process flow diagram of adaptive strategy state transition.

At the beginning of the evolution, all individuals are randomly distributed on a two-dimensional plane. Each individual is given a migration direction. The migration directions follow a uniform distribution over the range $(0, 2\pi)$. The initial strategy of an individual is chosen randomly among cooperative and defection strategies. Individuals are observed to change in position, strategy, and level of cooperation with the population during evolution.

3. Effect of Expectations and Weights on Strategy Evolution and Simulation Research

In a two-dimensional square plane with a number of individuals $N = 300$, side length $L = 10$, population density $\rho = N/L^2$, and periodic boundary conditions, individuals can migrate continuously in the plane. Initially, cooperative and defection strategies are uniformly and randomly distributed in the two-dimensional plane. In each round of the game, after each individual completes its interaction with its surrounding neighbors, the cumulative payoff is calculated based on the strategy choice. Because individuals are heterogeneous, a strategy adaptive algorithm based on expectations and node weights is proposed. It enhances the strength of the spatial reciprocity of the population structure. Individuals gain adaptability by regulating their social influence. Individuals with a high degree of adaptability have a greater chance of being imitated by others. After that, individuals decide whether to change their strategies based on whether they satisfy their expected payoff values. Satisfying the current state will not make a change. Otherwise, the individual chooses to learn the strategy of an individual with high influence in the surrounding neighborhood with probability p or migrate to another location with probability $1 - p$.

Firstly, the effect of node weights on cooperative evolution is analyzed. Figure 3 shows the variation in the cooperation rate f_c with evolution time for different gain factors r. Figure 3a shows the evolution curve for the expected strength A = 1 and the node weight strength value δ = 0.01. It can be seen from the figure that when $r < 4$, the evolution reaches a steady state when the cooperator cannot survive. This is because cooperators cannot gain enough payoff to defend against defectors at this time. As the gain factor r increases, cooperators are able to gain more. Cooperation also gradually increases in proportion in the network. The formed clusters of cooperators are able to resist the invasion of defectors. At the same time, more defectors are attracted to join the cluster of cooperators. Until gain factor $r > 6$, most individuals in the network are satisfied with their expectations and do not change their current state. As shown in Figure 3b, we adjust the moderate δ value to effectively promote cooperation when the weight intensity δ = 0.1. The cooperation rate rapidly drops to zero for a very small gain factor r. However, when $r > 3$, the adaptation of heterogeneous cooperative individuals rapidly increases to influence the surrounding neighbors due to the introduction of node weights in the model. The cooperation rate is promoted to be greatly improved.



(**a**) (**b**)

Figure 3. Evolutionary plots of system cooperation levels for different gain factors r, where (**a**,**b**) correspond to δ = 0.01 and δ = 0.1, respectively.

To further explain why this mechanism promotes cooperative behavior, Figure 4 shows the time evolution of the weight intensity δ for different values when the expectation value (A = 1) and the gain factor (r = 3) are fixed. Defectors are superior to cooperators in the early phase of the evolutionary process, regardless of the magnitude of the δ value. However, after this phase, the fate of evolution is completely different. The blue curve corresponds to the conventional case (δ = 0). In the absence of node weight effects, the cooperators in the network gradually disappear. When the weight intensity δ = 0.01, defectors occupy most of the network and only a small number of cooperators can coexist. For the weight intensity δ = 0.1, although cooperators decrease rapidly in the early phase, they gradually increase with the evolution of time. The cooperator clusters begin to expand, leading to a gradual increase in the level of cooperation. When finally stabilized, the cooperation rate reaches 0.76. The reason for this phenomenon is the introduction of the co-evolutionary model of game strategy and node weights into the traditional game, which enhances the competitiveness of the cooperators. Overall, our results show that node weights have a positive effect on the evolution of cooperation.

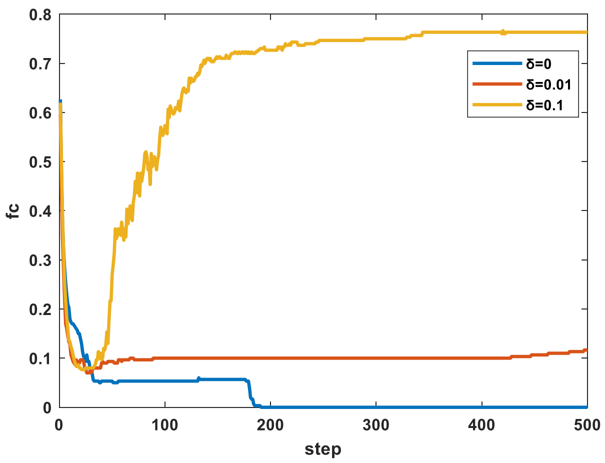


Figure 4. Time evolution of system cooperation level with different weight intensity δ.

Then, we investigate the evolution of cooperation where expectations and node weights act together within the whole range of the gain factor ($1 \leq r \leq 10$). In Figure 5, the variation in the cooperation rate f_c with the gain factor r for different values of the desired intensity A is shown. For the weight intensity δ = 0 (black curve in Figure 5), the model is equivalent to the conventional case. When no node weights are introduced, all individuals have the same adaptation value. For very small values of the gain factor r, the collaborator can still exist. The cooperation rate improves as r increases. However, when the gain factor is high ($r > 6$), all individuals meet the current expectation. The state of the individuals is not influenced by any factor. There is a mixture of cooperators and defectors in the space, which is not consistent with reality. By introducing node weights and expectation effects, the existence of cooperative evolutionary situations in reality can be better explained.

Focusing on the case of the weight intensity δ = 0.01, the evolution of cooperation performs better than the conventional case. Interestingly, a moderate value of the desired intensity A ($A = 2$) promotes cooperation most effectively. Although cooperators enter an all-defector state for the whole system when the value of r is small, cooperators rapidly occupy the survival space as r continues to increase. This phenomenon is common for different values of the desired intensity A. In the majority of cases, the algorithm is able to significantly reduce the threshold of cooperative evolution. In particular, when an individual uses this algorithm to regulate the social influence of interacting individuals, the individual only uses the local interaction information. In particular, when an individual uses this algorithm to regulate the social influence of interacting individuals, the individual only uses the local interaction information, such as the interacting object, the imitation object, and the expected payoff with them. This algorithm coincides to some extent with the pattern of construction of human social connections. People with high influence in society are more likely to be followed and imitated by everyone. Social connections are made between them. In particular, structural clusters in social networks increase as individuals regulate their social connections. This suggests that structural clusters in social networks facilitate the evolution of cooperative behavior.

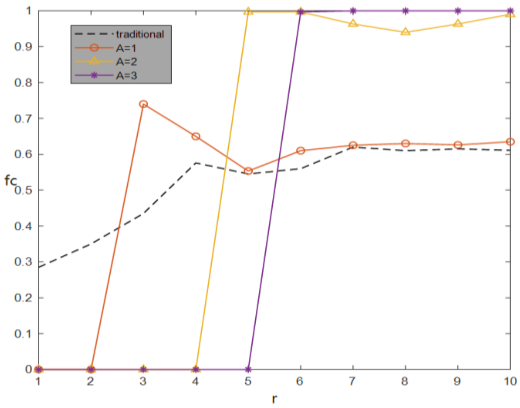


Figure 5. Evolution of the cooperation rate f_c with the gain factor r for different values of the desired intensity A.

4. Evolution of Cooperation in Spatial Games and Simulation Research

In this section, the evolution starts from a specific initial state to explore the evolution of cooperation more clearly. Figure 6 depicts the distribution of discrete individuals in the two-dimensional plane as they evolve and migrate using different time strategies. Specifically, blue represents cooperators, and red represents defectors. Additionally, connecting lines represent the relationship between individuals and their neighbors.

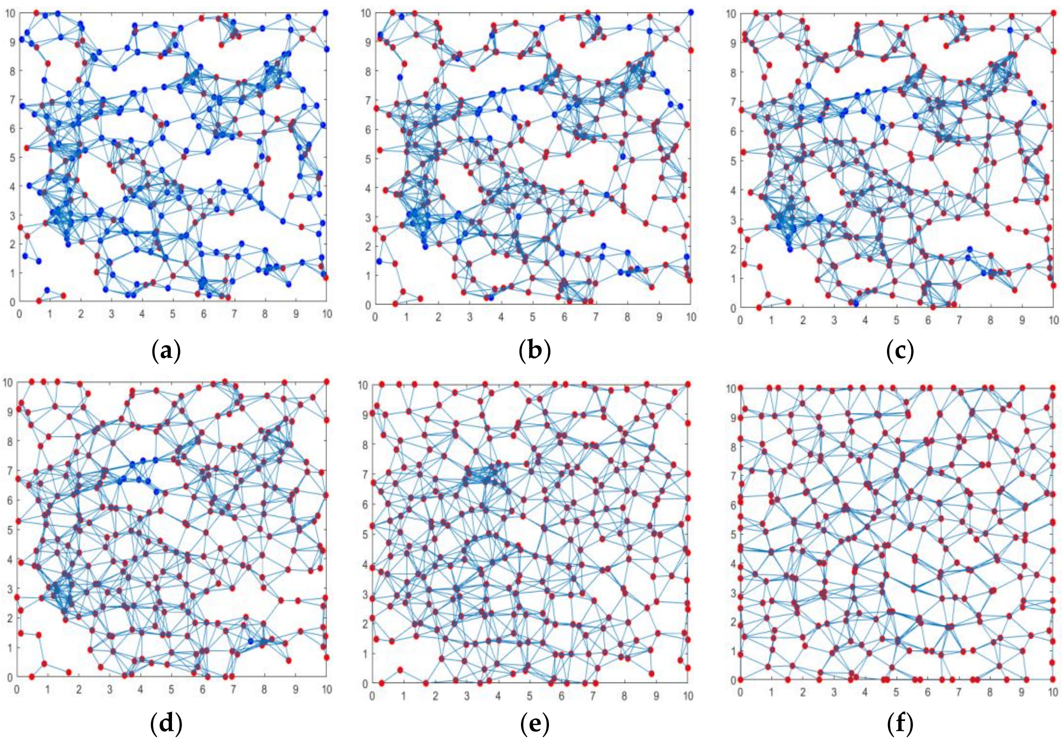


Figure 6. Defector model evolution process. (**a**) t = 0; (**b**) t = 20; (**c**) t = 60; (**d**) t = 100; (**e**) t = 150; (**f**) t = 200.

At the beginning of the evolution, all player node weights are set to one. Each player is set as a cooperator or a defector by a random function. We use a combination of expectations and node weights for the evolution of the system. As shown in Figure 6, for the traditional case (δ = 0), the defectors around the cooperator cluster increase rapidly due to the advantage of gains. As shown in Figure 6b, defectors increase rapidly. The cooperators gradually decrease. Thus, from Figure 6c–e, the red individuals occupy most of the network. Only a small portion of the cooperator clusters survives. Due to the high adaptation of defectors around the cooperator clusters, the cooperator clusters are broken into smaller clusters until all cooperators eventually disappear. In Figure 6f, because of the repulsive effect among defectors, a solid triangular network is formed among the defecting individuals.

Therefore, when no node weights are introduced, the cooperators cannot form tight clusters to resist the invasion of betrayers. After some time, the cooperators disappear. As shown in Figure 7, the initial evolution of cooperation is similar to the conventional case when the expected intensity $A = 3$ and the appropriate weight intensity δ = 0.01. The proportion of cooperators decreases rapidly. The red defectors easily invade the blue cooperators. Only a few cooperators survive by forming a few small cooperative clusters. However, as shown in Figure 7b, we can find that the situation is reversed. Highly weighted cooperators survive by forming small and tight clusters of cooperators. The average node weights of the cooperators in clusters increase. In a small area full of defectors, the payoff of defectors is equal to zero, which is less than the desired value. As a result, the weight of the defectors keeps decreasing. Then, the blue areas unfold and merge to form larger clusters to invade the space occupied by the defectors. It can be observed that the blue cooperators invade all the red defectors. From Figure 7c–e, the area of blue collaborators gradually expands. From Figure 7f, it can be observed that the blue cooperators form clusters and effectively resist the invasion of betrayers. This phenomenon suggests that cooperators can reverse the weakness of the strategy by preventing the invasion of defectors through the high-weighted cooperator clusters.

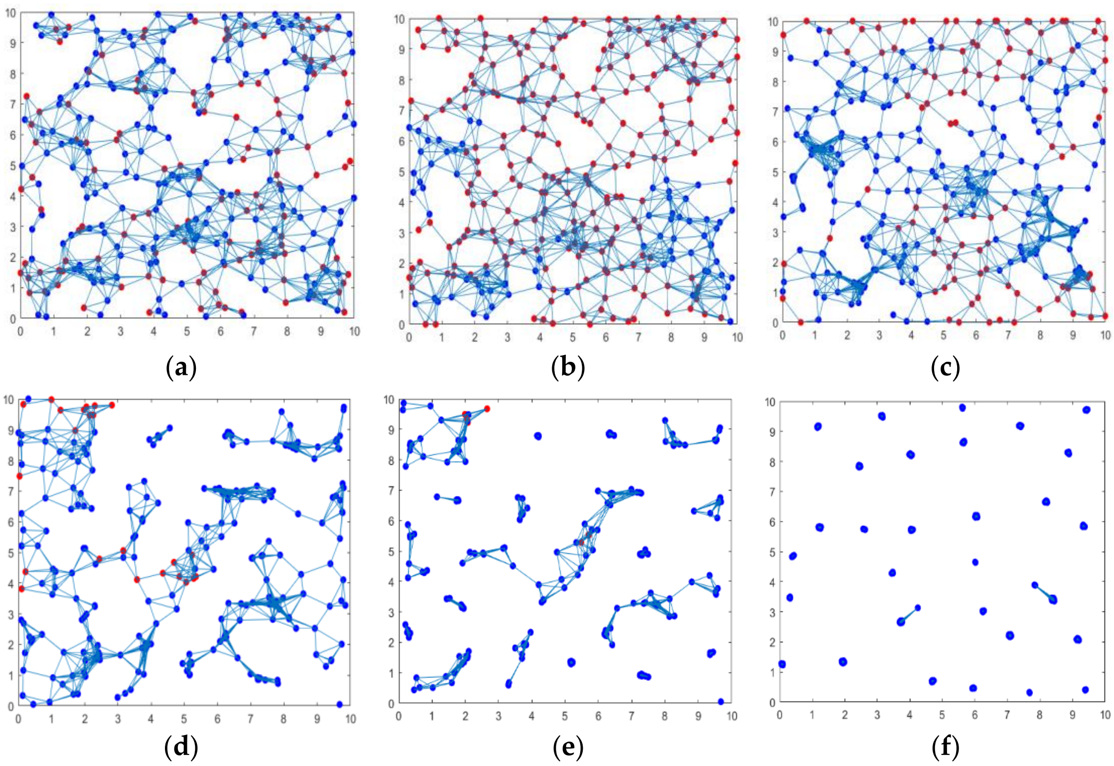


Figure 7. Evolutionary process of cooperator model. (**a**) t = 0; (**b**) t = 20; (**c**) t = 60; (**d**) t = 100; (**e**) t = 150; (**f**) t = 200.

5. Effect of Population Density on Strategy Evolution and Simulation Research

Through the above analysis, in the adaptive game, the cooperator can gain more than the defector when the gain factor r is large enough, which motivates defectors to learn the cooperative strategy. We note that for a low spatial density, the cooperators are able to occupy the whole network under the effect of node weights. It becomes the ultimate evolutionarily stable strategy. This is because information is communicated among sparser individuals, which facilitates cooperators to resist defectors' invasion. To better explore the interactions between cooperators and defectors, we next turn to how the quantitative relationship of the cluster affects cooperative evolution. Because it is difficult to theoretically analyze a phenomenon that generates cooperative optimality, we resort to numerical simulations to explain it.

As shown in Figure 8a, at the beginning of the evolutionary stage, the cooperation rate f_c decreases rapidly in all cases due to the random distribution of strategies and the gain advantage of defectors. In the next 10 to 200 steps of the evolutionary stage, it is advantageous for cooperators when the gain factor is relatively large ($r > 4$). The proportion of cooperators gradually increases. A state of dynamic equilibrium is reached. At this time, the proportion of cooperators is close to one. Most individuals are selfish. As the population density increases, everyone tends to move in their own favorable direction, so defectors dominate the network. From Figure 8b,c, it can be seen that when the gain factor is small, the space is quickly occupied by defectors. The cooperators quickly drop to zero. However, our model introduces node weights. When the gain factor is large enough, the gain satisfies the expectation of the cooperators. The degree of adaptation keeps increasing. The cooperators are highly adaptive. Under a high density, individuals can still perform adaptive migration and resist the defectors' invasion. Additionally, imitated by the strategies of other neighbors, the cooperator's state keeps increasing and reverses the disadvantageous position occupied by the cooperator.

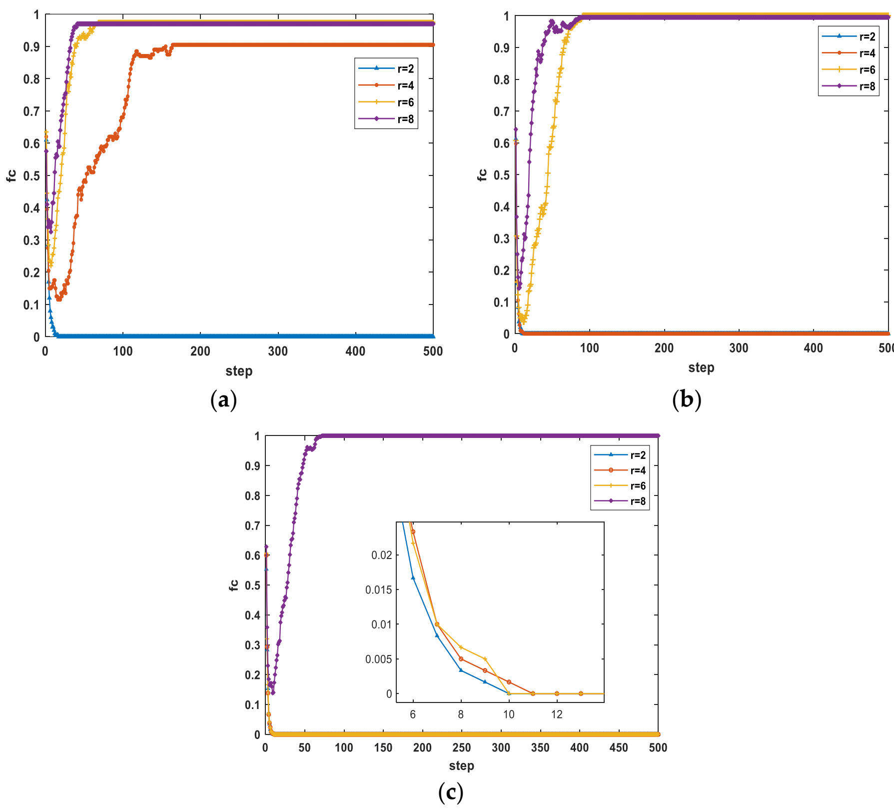


Figure 8. Relationship between population density and cooperative evolution: (**a**) ρ = 2, (**b**) ρ = 4, and (**c**) ρ = 6.

6. Conclusions

Social relationship heterogeneity promotes the evolution of cooperation in social dilemmas. Group interactions in structured populations may be much greater than the corresponding two-by-two interactions. In behavioral science, individuals evaluate gains by comparing their levels of expectation. Inspired by this, the node weights are linked to the individual's expectations. A player's weight increases only when the gain from a neighbor exceeds his or her expectation. Conversely, if this goal is not achieved, the player's weight decreases. In this paper, the effect of expectation and node weight co-evolution on the evolution of strategic cooperation was investigated in a public goods game with strategic adaptation. Additionally, through multi-agent dynamic simulations, we found that this mechanism can effectively facilitate the evolution of cooperation. The results show that appropriate weight intensity δ values can induce the emergence of high levels of cooperation. The cooperation facilitation mechanism relies on the spontaneous emergence of a dynamic invasion process. Finally, we also explored the effect of population density on the evolution of cooperation. Although the gain factor r can promote the emergence of cooperative strategies and inhibit the emergence of defectors to better promote cluster behavior, the higher the population density, the less favorable it is for the survival and development of cooperators. All these results reveal the connection between individual and group levels and interests in collective behaviors with different social relations.

By studying the emergence mechanism of cooperative behavior in spatial games, we revealed the mechanism underlying the emergence of large-scale cooperative behavior and the self-organization phenomenon. We analyzed the distribution characteristics of cooperative behavior of games in various scenarios and further revealed the evolution law of group cooperative behavior. This research direction has wide application in both the information and engineering fields. Under the theoretical framework of information games, the strategy update of individual nodes in the network can promote network reciprocity, thus completing the system decision-making process. Therefore, how to guide and control the group decision-making process has become a research hotspot in network science and one of the top twenty challenges in the 21st century listed by *Science*. Current research is basically based on numerical computer simulation methods for prediction, which are not applicable to more complex topologies, and there are still many problems to be further addressed. Therefore, the search for more effective theoretical methods and analytical tools will make a significant contribution to future research on the intelligent decision-making and coordinated organization of multiple agents.

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Conflicts of Interest: The authors declare no conflict of interest.

References

1. Nowak, M.A. Five Rules for the Evolution of Cooperation. *Science* **2006**, *314*, 1560–1563. [CrossRef] [PubMed]
2. Tilman, A.R.; Plotkin, J.B.; Akçay, E. Evolutionary games with environmental feedbacks. *Nat. Commun.* **2020**, *11*, 915. [CrossRef] [PubMed]
3. Hauert, C.; Saade, C.; McAvoy, A. Asymmetric evolutionary games with environmental feedback. *J. Theor. Biol.* **2019**, *462*, 347–360. [CrossRef] [PubMed]
4. Biro, D.; Sasaki, T.; Portugal, S. Bringing a Time–Depth Perspective to Collective Animal Behaviour. *Trends Ecol. Evol.* **2016**, *31*, 550–562. [CrossRef]
5. Tanimoto, J. *Fundamentals of Evolutionary Game Theory and Its Applications*; Springer: Tokyo, Japan, 2015. [CrossRef]
6. Nepusz, T.; Vicsek, T. Controlling edge dynamics in complex networks. *Nat. Phys.* **2012**, *8*, 568–573. [CrossRef]

7. Scholtes, I.; Wider, N.; Pfitzner, R.; Garas, A.; Tessone, C.J.; Schweitzer, F. Causality-driven slow-down and speed-up of diffusion in non-Markovian temporal networks. *Nat. Commun.* **2013**, *5*, 5024. [CrossRef]
8. Helbing, D.; Yu, W. The outbreak of cooperation among success-driven individuals under noisy conditions. *Proc. Natl. Acad. Sci. USA* **2009**, *106*, 3680–3685. [CrossRef]
9. Gräser, O.; Xu, C.; Hui, P.M. Analytic approach to co-evolving dynamics in complex networks: Dissatisfied adaptive snowdrift game. *New J. Phys.* **2011**, *13*, 083015. [CrossRef]
10. Wu, B.; Da, Z.; Feng, F.; Luo, Q.; Long, W.; Traulsen, A. Evolution of Cooperation on Stochastic Dynamical Networks. *PLoS ONE* **2010**, *5*, e11187. [CrossRef]
11. Cardillo, A.; Petri, G.; Nicosia, V.; Sinatra, R.; Gómez-Gardeñes, J.; Latora, V. Evolutionary dynamics of time-resolved social interactions. *Phys. Rev. E* **2014**, *90*, 052825. [CrossRef]
12. Choi, J.-K.; Bowles, S. The Coevolution of Parochial Altruism and War. *Science* **2007**, *318*, 636–640. [CrossRef] [PubMed]
13. Fehr, E.; Schmidt, K.M. A Theory of Fairness, Competition, and Cooperation. *Q. J. Econ.* **1999**, *114*, 817–868. [CrossRef]
14. Dawes, C.T.; Fowler, J.; Johnson, T.; McElreath, R.; Smirnov, O. Egalitarian motives in humans. *Nature* **2007**, *446*, 794–796. [CrossRef] [PubMed]
15. Szolnoki, A.; Xie, N.-G.; Wang, C.; Perc, M. Imitating emotions instead of strategies in spatial games elevates social welfare. *Eur. Lett.* **2011**, *96*, 38002. [CrossRef]
16. Szolnoki, A.; Xie, N.-G.; Ye, Y.; Perc, M. Evolution of emotions on networks leads to the evolution of cooperation in social dilemmas. *Phys. Rev. E* **2013**, *87*, 042805. [CrossRef]
17. Gross, T.; D'Lima, C.J.D.; Blasius, B. Epidemic Dynamics on an Adaptive Network. *Phys. Rev. Lett.* **2005**, *96*, 208701. [CrossRef]
18. Sahni, N.; Yi, S.; Taipale, M.; Bass, J.I.F.; Coulombe-Huntington, J.; Yang, F.; Peng, J.; Weile, J.; Karras, G.; Wang, Y.; et al. Widespread Macromolecular Interaction Perturbations in Human Genetic Disorders. *Cell* **2015**, *161*, 647–660. [CrossRef]
19. King, A.J.; Fehlmann, G.; Biro, D.; Ward, A.; Fürtbauer, I. Re-wilding Collective Behaviour: An Ecological Perspective. *Trends Ecol. Evol.* **2018**, *33*, 347–357. [CrossRef]
20. Wang, J.; Hong, Y.; Wang, J.; Xu, J.; Tang, Y.; Han, Q.-L.; Kurths, J. Cooperative and Competitive Multi-Agent Systems: From Optimization to Games. *IEEE/CAA J. Autom. Sin.* **2022**, *9*, 763–783. [CrossRef]
21. Delgado, M.D.M.; Miranda, M.; Alvarez, S.; Gurarie, E.; Fagan, W.F.; Penteriani, V.; di Virgilio, A.; Morales, J.M. The importance of individual variation in the dynamics of animal collective movements. *Philos. Trans. R. Soc. B Biol. Sci.* **2018**, *373*, 20170008. [CrossRef]
22. Farine, D.R.; Strandburg-Peshkin, A.; Couzin, I.; Berger-Wolf, T.Y.; Crofoot, M.C. Individual variation in local interaction rules can explain emergent patterns of spatial organization in wild baboons. *Proc. R. Soc. B Boil. Sci.* **2017**, *284*, 20162243. [CrossRef] [PubMed]
23. Farine, D.R.; Strandburg-Peshkin, A.; Berger-Wolf, T.; Ziebart, B.; Brugere, I.; Li, J.; Crofoot, M.C. Both Nearest Neighbours and Long-term Affiliates Predict Individual Locations During Collective Movement in Wild Baboons. *Sci. Rep.* **2016**, *6*, 27704. [CrossRef] [PubMed]
24. Roca, C.P.; Helbing, D. Emergence of social cohesion in a model society of greedy, mobile individuals. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 11370–11374. [CrossRef]
25. Li, X.; Hao, G.; Zhang, Z.; Xia, C. Evolution of cooperation in heterogeneously stochastic interactions. *Chaos Solitons Fractals* **2021**, *150*, 111186. [CrossRef]
26. Sueur, C.; Petit, O.; Deneubourg, J.L. Short-term group fission processes in macaques: A social networking approach. *J. Exp. Biol.* **2010**, *213*, 1338–1346. [CrossRef]
27. Bode, N.W.; Wood, A.J.; Franks, D.W. The impact of social networks on animal collective motion. *Anim. Behav.* **2011**, *82*, 29–38. [CrossRef]
28. Miguel, M.C.; Parley, J.T.; Pastor-Satorras, R. Effects of Heterogeneous Social Interactions on Flocking Dynamics. *Phys. Rev. Lett.* **2018**, *120*, 068303. [CrossRef]
29. Shen, C.; Chu, C.; Guo, H.; Shi, L.; Duan, J. Coevolution of Vertex Weights Resolves Social Dilemma in Spatial Networks. *Sci. Rep.* **2017**, *7*, 15213. [CrossRef]