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Effect of migration based on strategy and cost on the evolution of cooperation

Yan Li *, Hang Ye

School of Economics, Zhejiang University, Hangzhou 310027, China
Interdisciplinary Center for Social Sciences, Zhejiang University, Hangzhou 310027, China

A R T I C L E I N F O

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A B S T R A C T

Humans consider not only their own ability but also the environment around them during the process of migration. Based on this fact, we introduce migration based on strategy and cost into the Spatial Prisoner's Dilemma Game on a two-dimensional grid. The migration means that agents cannot move when all of the neighbors are cooperators; otherwise, agents move with a probability related to payoff and cost. The result obtained by the computer simulation shows that the moving mechanism based on strategy and cost improves the level of cooperation in a wide parameter space. This occurs because movement based on strategy effectively keeps the cooperative clusters and because movement based on cost effectively regulates the rate of movement. Both types of movement provide a favorable guarantee for the evolution of stable cooperation under the mutation rate $q = 0.0$. In addition, we discuss the effectiveness of the migration mechanism in the evolution of cooperation under the mutation rate $q = 0.001$. The result indicates that a higher level of cooperation is obtained at a lower migration cost, whereas cooperation is suppressed at a higher migration cost. Our work may provide an effective method for understanding the emergence of cooperation in our society.

1. Introduction

The Prisoner's Dilemma Game tells us that the payoff for defectors is higher than that for cooperators, which leads to defection in a Nash equilibrium based on selfish players. However, cooperation is widespread in social and biological systems, which is called the social dilemma. How to resolve this dilemma has become a hot issue in recent decades in the areas of economics, physics and biology [1–3]. The evolutionary game is a theoretical tool used in cooperation research, and two significant books have been published on the topic: Evolution and the Theory of Games [4] and The Evolution of Cooperation [5]. A popular research method for studying cooperation is computer simulation based on agents. Experimental economics is another important tool [6–11]. Nowak puts forward five angles to discuss the emergence of cooperation: kin selection, direct reciprocity, indirect reciprocity, group selection and spatial structure [12,13], in which spatial structure is an important aspect. The purpose of the research based on spatial structure is to discuss what types of spatial structure and evolutionary mechanisms are favorable for the promotion of cooperation. Spatial structure, or network topology, plays an important role in our social and economical life, particularly in the transmission of information [14]. The main reason why spatial structure promotes the emergence of cooperative behavior is that it provides a profitable context for clusters of cooperators [13]. The research on facilitating cooperation based on network topology includes three main aspects. The first such aspect is the influence of spatial structure, including its types and properties, on the evolution of cooperation. The regular lattice [15–17], the random

* Corresponding author at: School of Economics, Zhejiang University, Hangzhou 310027, China. Tel.: +86 13567135967; fax: +86 57188273516.
E-mail address: liyan5199@163.com (Y. Li).

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network [18], the small world network [19,20] and the scale-free network [21–24] are the four most commonly used network types. The properties of a network include the distribution of degree [25], average path length, clustering coefficient, positive assortativity and community structure [14]. Second, some works are aimed at exploring the effects of the heterogeneity of players [26,27], such as the limited memory of agents [28], age-related vitality of players [29,30], and different influences of players [26,31,32]. The last aspect is the influence of the co-evolution of network topology and strategy on the evolution of cooperation [13,33,34], such as the co-evolution of network topology and strategy based on reputation [35] and the co-evolution of spatial structure and strategy dependent on random mobility [36]. Different game types, including the Prisoner's Dilemma Game [15,37], Hawk-dove game [16], Stag Hunt game [38], Public Goods game [2,39], different strategy-updating rules [23,26,40–44] and different payoff functions [45–51], are also related to the promotion of cooperation. The co-evolution of network topology and strategy is closer to reality. The migration of agents is an important method for the formation of co-evolution and cooperative clumps [52–57].

Migration has a dual function in the evolution of cooperation. On the one hand, cooperators can move forward to the cooperative clumps by escaping from defectors, which results in the promotion of cooperation [52]. In other words, because cooperators have more opportunities to interact with each other than with defectors, cooperation is favored by the natural selection, which is a phenomenon known as positive assortment. On the other hand, defectors can achieve a higher payoff by moving to the cooperators, which results in the collapse of cooperation [58]. Therefore, migration has different influences on the evolution of cooperation under different conditions and different mechanisms, which is why many works are devoted to discussing the effect of migration on the evolution of cooperation. Over the past decades, five main mobility mechanisms have been used to study the influence of migration on the evolution of cooperation: related to payoff [59–62], associated with strategy [53,54,63], random migration on a two-dimensional plane [64,65], risk-driven migration [66] and dissatisfaction-driven migration[61]. Previous studies investigating the influence of movement on the evolution of cooperation have focused on density of individuals [67–69], rate of mobility [64,65] and scope of migration [70–72].

Cost is another essential factor in the process of migration. For example, both the agents that move from one place to another and the agents that keep or cut links with their partners need fees. However, the influence of cost on the evolution of cooperation has been rarely discussed in the migration mechanism. The research of previous works [3,73] reveals that migration cost reduces the dynamic of network topology but does not suppress the emergence of cooperative behavior. As known, humans, when moving, consider not only their own ability but also the environment around them. Generally speaking, individuals are not able to move when they find that their neighbors are all cooperators, irrespective of their own behavior. In addition, individuals are not able to move without considering their payoff and migration costs when there are defectors around them. The probability of migration is dependent on payoff and cost. The migration costs include the fees of agents moving from one place to another. Generally, a larger payoff results in a greater possibility of migration, and a higher cost results in a lower possibility of migration. An agent whose payoff is higher has high ability to improve his living environment. For example, a cooperator who has two cooperator neighbors obtains higher payoff than a cooperator who only has one cooperator neighbor, thus having more possibility to search three or four cooperator neighbors. In summary, we put forward a migration mechanism based on strategy and cost, which means that agents cannot move when all of the neighbors are cooperators. Otherwise, agents move with a probability related to payoff and cost. The results obtained from the computer simulation indicate that it is favorable for the emergence of cooperation in a wide parameter space.

The rest of the paper is organized as follows. We present our Spatial Prisoner's Dilemma Game model with the introduction of migration based on strategy and cost in Section 2. In Section 3, we depict the simulation results based on the model in Section 2. Finally, we summarize the main conclusions in Section 4.

2. Model

We assume that each player is placed on a regular $L \times L$ lattice with periodic boundary conditions and Von Neuman neighborhood. Each site is vacant or occupied by one player. Agents designated as cooperators or defectors with equal probability are randomly distributed in spatial structure. Given that the total number of agents is N, we define $\rho = N/L \times L$ as the density of population, which indicates the fraction of non-vacant places.

Next, we briefly describe the Spatial Prisoner's Dilemma Game, which is a classic representation of social dilemma. Each player i, who is either a cooperator or a defector, obtains his total payoff P_i by playing games with his neighbors, who belong to Ω_i, which represents the set of all neighbors of agent i. We set A as the payoff matrix as follows:

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} R & S \\ T & P \end{pmatrix} \end{array} \tag{1}$$

where C and D are cooperate and defect, respectively. R is the payoff of the agents when they are both cooperators, and P is the payoff of the agents when they are both defectors. S and T are the payoffs of cooperator and defector when one agent is a cooperator and another is a defector, respectively. Because PDG satisfies the condition that is

$T > R > P > S$, (D, D) is the only Nash equilibrium. The parameters are assumed to be $R = 1.0$, $S = 0.0$, $T = b$, $P = 0.1$ according to [74,75]. We give the function of payoff as follows:

$$P_i = \sum_{j \in \Omega_i} u_i' A u_j, u_i^C = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \quad u_i^D = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \tag{2}$$

where u_i^C and u_i^D mean that the strategies of a player are cooperation and defection, respectively. The strategies of player i and its neighbor j are u_i and u_j, respectively. The transpose of the state vector u_i is u_i'.

We discuss the influence of migration based on strategy and cost on the evolution of cooperation in our context. The migration mechanism means that agent cannot move when he finds that all of the neighbors are cooperators; otherwise, the agent moves with a probability υ_i, called the migration rate of agent i.

$$\upsilon_i = \begin{cases} 0, & N_D = 0 \\ d \times \frac{P_i}{P_i + c}, & otherwise \end{cases} \tag{3}$$

In formula (3), N_D is the number of defectors in the agent's neighborhood, and d is the control parameter that can be interpreted as the risk preference of the agent; it is given the value of 0.5 because all agents are considered homogeneous in our context. Parameter c is the migration cost.

The model can be divided into four parts as follows:

(1) The game

Each agent plays the Prisoner's Dilemma Game with his neighbors, and the payoff is calculated according to formula (2), except for the isolated agent, whose payoff is set to be 0. Another point worth mentioning is that we reset the payoff of all agents to be 0 in the next time step. In other words, an agent cannot accumulate food and storage resources in any way, and all reproduction is consumed in one step, which is a classic economics characteristic in a hunter-gatherer society [2,76–77].

(2) The strategy update

The agent copies the strategy of the richest neighbor, except when the focal agent is the richest one. In that case, the focal agent's strategy remains unchanged. We adopt an asynchronous fashion in updating process.

(3) The migration

The agent moves according to formula (3).

(4) The mutation

Every agent has a chance to change his strategy to the opposite one with a small probability q, which is defined as the mutation rate [78]. In our text, we consider two situations: one is $q = 0.0$ and the other is $q = 0.001$.

The computer simulation procedure of our model is as follows:

```
Initialize
For each time step:
  For each agent:
    Interacts with his Von Neuman neighbors and
   calculates his payoff.
  End
  For each agent:
    Learns strategy according to the richest rule.
    Migrates according to strategy and cost.
  End
  For each agent:
    Mutates with probability q.
  End
End
```

3. Results

First, we investigate the effectiveness of the migration based on strategy and cost for the evolution of cooperative behavior. The evolution result of cooperative behavior is primarily reflected in the proportion of cooperators in the population size. The level of cooperation can be expressed as $f_c = N_C/N$, when the numbers of cooperators and all individuals are assumed to be N_C and N, respectively. A proportion of cooperators as 0.5 is given as initial state. Fig. 1 shows the number of cooperators over time under the migration based on strategy and cost. The simulation results show that the migration based on strategy and cost promotes the emergence of cooperative behavior and improves the level of cooperation in a wide parameter space. Fig. 1(a) and (c) show the evolution of cooperation under different b and c values in the case of no mutation. It is shown that the number of cooperators first drops rapidly and experiences a brief vibration in the early evolution; the level of cooperation then gradually shows a steady state at approximately 0.8, independent of the b and c values. Fig. 1(b) and (d) show the evolution of cooperation with $q = 0.001$. They indicate that although the level of cooperation decreases accordingly with the increasing cost, the cooperative behavior can still emerge at a higher cost. This further shows that the migration based on strategy and cost greatly promotes the evolution of cooperation. The promotion of cooperation under the migration mechanism is due to two primary reasons. On the one hand, movement based on strategy effectively keeps the cooperative clusters, which provides favorable conditions for the expansion of cooperation. On the other hand, moving based on cost effectively regulates the rate of movement, which decreases the possibility of defectors looking for cooperators, thereby reducing the chance of defectors invading cooperators. Both movement types provide a favorable guarantee for the evolution of stable cooperation under the mutation rate $q = 0.0$.

Fig. 2 shows the effect of the density ρ on the evolution of cooperation under the migration based on strategy and cost. The results show that there is an optimal density value that makes the level of cooperation reach the maximum for different values of b. The level of cooperation reaches a maximum of approximately 0.94 when the density value is approximately 0.8 for both $b = 1.2$ and $b = 1.3$, with $q = 0.001$. For $b = 1.4$, the level of cooperation reaches approximately 0.7 when the density value is approximately 0.7 because a density value that is too small or too large will make the migration based on strategy and cost fail and play no significant role in the emergence of cooperation. A concrete analysis is given for the result when $q = 0.0$ and $b = 1.4$. Most of the isolated agents exist in space when $\rho = 0.1$, leading to little possibility of a game between them. Moreover, the cooperators playing the game with defectors will change their strategy during the process of strategy update. Therefore, the level of cooperation is slightly lower than that in initial state. Under the condition that $\rho \in (0.1, 0.4)$, with the increase in density values, the opportunity of the game between individuals increases, but not enough small cooperative clusters can form. Therefore, more cooperators turn into defectors

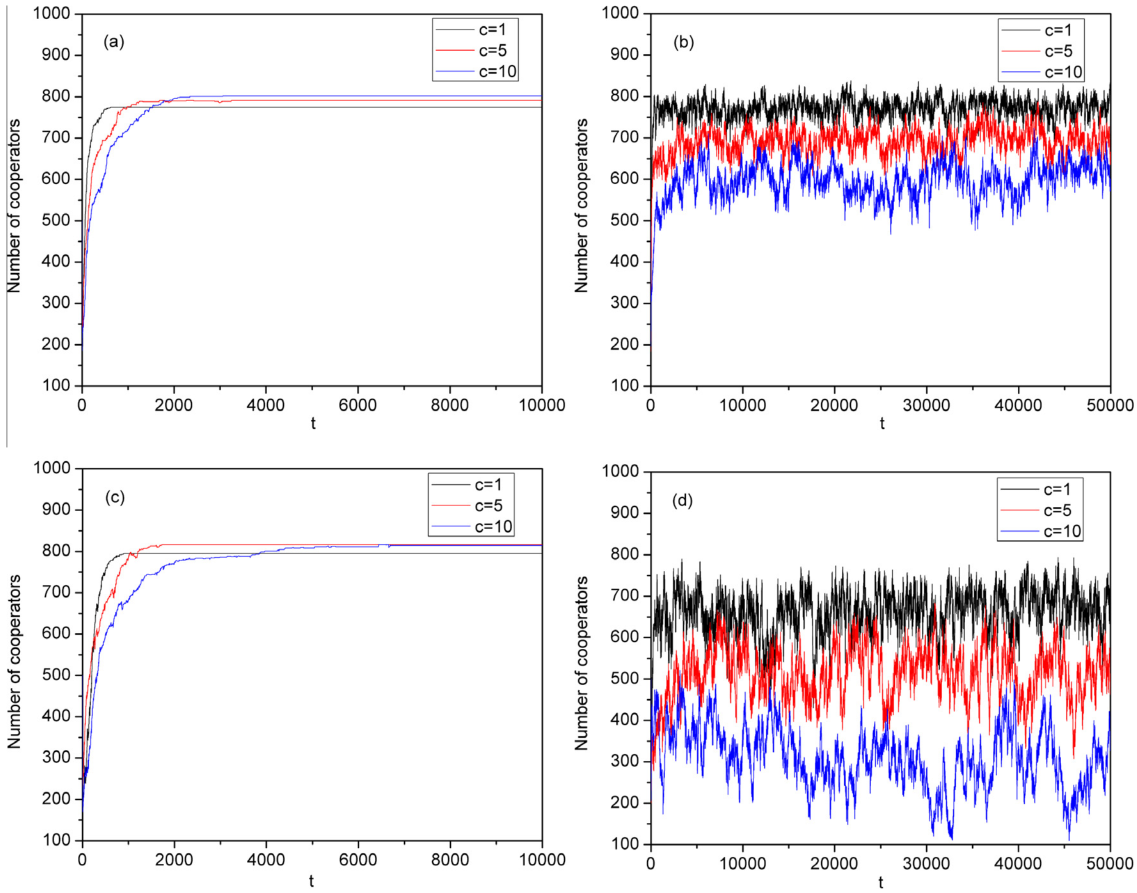

Fig. 1. The number of cooperators as a function of time step t. (a) $q = 0.0$, $b = 1.2$, (b) $q = 0.001$, $b = 1.2$, (c) $q = 0.0$, $b = 1.4$, (d) $q = 0.001$, $b = 1.4$. Other parameters: $\rho = 0.625$, $d = 0.5$, $N = 1000$.

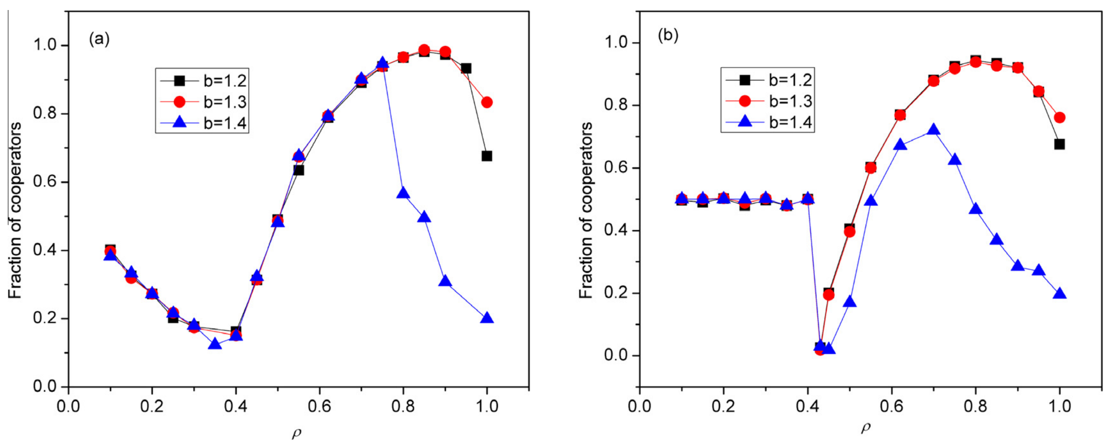

Fig. 2. Fraction of cooperators f_c as a function of ρ for different defection parameters b. (a) $q = 0.0$, (b) $q = 0.001$. Other parameters: $L = 40$, $d = 0.5$, $c = 1$. Each data point is obtained after averaging over 20 independent runs, and the fraction of cooperators is obtained by averaging over 500 time steps after 9500 time steps for $q = 0.0$. The fraction of cooperators is obtained by averaging over 10,000 time steps after 100,000 time steps for $q = 0.001$.

during the strategy update, which leads to a reduction in the level of cooperation. The migration mechanism that is dependent on strategy and cost becomes effective for the promotion of cooperation when $\rho \in (0.4, 0.7)$ because with the increase in density ρ, there are enough cooperators to meet each other, and a certain number of vacant sites is beneficial for the cooperators escaping from defectors. However, when the density value is so large that the empty sites hardly exist, the cooperators cannot escape from defectors. Therefore, the cooperation level decreases when $\rho > 0.7$. A similar situation exists for $b = 1.2$ and $b = 1.3$. The evolution trend of the cooperation level when $q = 0.001$ and $\rho > 0.5$ is almost the same as that when $q = 0.0$. The proportion of cooperators is approximately 0.5 when $\rho \in (0.1, 0.4)$, and the level of cooperation drops sharply when $\rho = 0.5$.

There are two reasons for the result when $\rho < 0.5$. On the one hand, most of agents exist in a form of small clusters or are isolated in spatial structure, thus making many cooperators turn into defectors. On the other hand, the introduction of mutation makes the defectors become cooperators. These two aspects balance each other and thus allow the cooperation level to maintain a fraction as the initial state. Nevertheless, more cooperators become defectors, leading to a sharp decline in the cooperation level when $\rho = 0.5$.

Fig. 3 shows the effect of the density ρ on the evolution of cooperation when the isolated agents can move properly. Compared with Fig. 2, the level of cooperation shows dramatical difference, especially for a small density of population. Similarly, there are also optimal densities that make the level of cooperation reach the maximum for different values of b. However, when $q = 0.0$ and $b = 1.2$, the level of cooperation is almost 0 when $\rho \in (0.1, 0.2)$. The reason is that the movement of the isolated agents makes more isolated cooperators become defectors during the strategy update, leading to the extinction of cooperators. The cooperation level increases when $\rho \in (0.2, 0.4)$, and it is close to 1 when $\rho \in (0.4, 0.9)$. This is because the migration of isolated cooperators enlarges the cooperative clusters, leading to the high level of cooperation. If $q = 0.0$ and $b = 1.4$, the cooperation cannot emerge when $\rho \in (0.2, 0.4)$ because the larger b makes more cooperators become defectors. The shape of the curves when $q = 0.001$ is almost the same as that when $q = 0.0$. We assume the isolated agents as static in the following discussion because the shape of the curves for other parameters makes no difference whether the isolated agents can move or not.

Fig. 4 shows the trend of cooperation level with the change in c values for different payoff parameters. First, it can be observed that the level of cooperation at $q = 0.0$ is significantly higher than that at $q = 0.001$, particularly when the value of c is higher. Second, increased costs have no significant effect on the level of cooperation with no mutation ($q = 0.0$) when all other variables are held constant. The level of cooperation is still approximately 0.8, even if the cost is higher. The level of cooperation gradually reduces until it tends to 0, along with the increase in cost when $q = 0.001$.

The reasons for the first result are analyzed below. The distribution of cooperators and defectors in the spatial structure are divided into three types, along with the evolution of cooperation. First, an agent exists in small clusters that are primarily composed of cooperators. Second, an agent is located in the small clusters that consist mainly of defectors. Third, cooperators and defectors are randomly distributed around the agent; in this case, the effects of the mutation rate on the evolution of cooperation are determined by the randomness. When cooperators turn into defectors during the mutation process, not only is the number of cooperators reduced, but the strategy is also changed in the next round. In the case when the mutant is located in the first type of space state (cluster composed of cooperators), his next game return is higher than those other cooperators, leading other cooperators to turn into defectors during the learning strategies. This situation greatly undermines the clusters of cooperators and reduces the level of cooperation. In the case when the mutant exists in the second type of space state (small cluster composed of defectors), his strategy is same as his neighbors'. Therefore, the number of cooperators is not affected in the next round of strategy simulation. In summary, a cooperator turning into a defector not only reduces the number of cooperators but also increases the opportunity for defectors to invade cooperators, resulting in a decline in the cooperation level. When defectors turn into cooperators during the mutation process, the number of

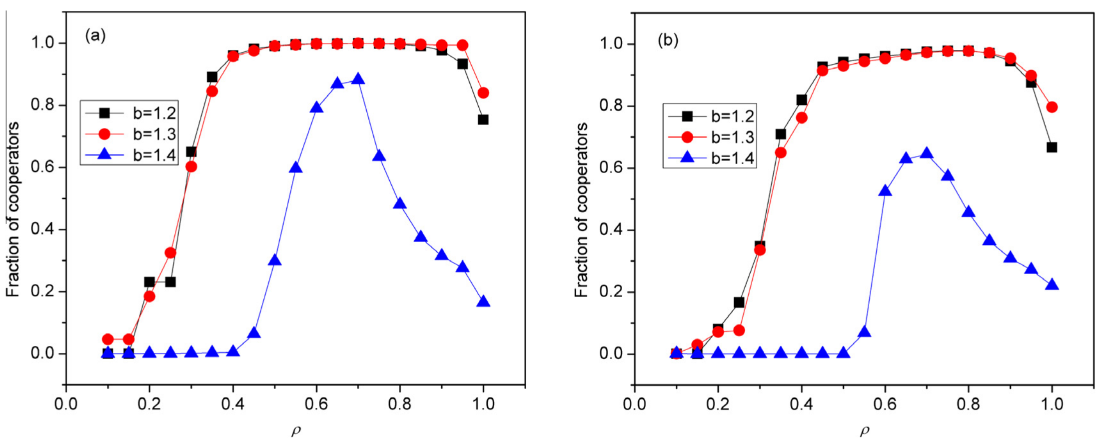

Fig. 3. Fraction of cooperators f_c as a function of ρ for different defection parameters b when the isolated agents can move properly. (a) $q = 0.0$, (b) $q = 0.001$. Other parameters: $L = 40$, $d = 0.5$, $c = 1$. The data points are obtained in the same way as in Fig. 2.

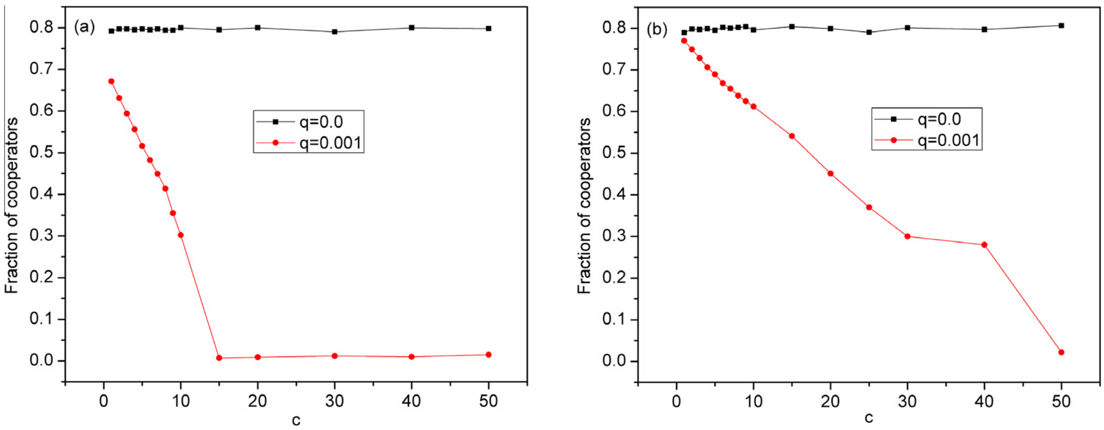

Fig. 4. Fraction of cooperators f_c as a function of c for different mutation rates q. (a) $b = 1.4$, (b) $b = 1.2$. Other parameters: $\rho = 0.625$, $d = 0.5$, $N = 1000$. The data points are obtained in the same way as in Fig. 2.

cooperators increases superficially, but the increase in the level of cooperation is very small because of the smaller mutation rate. The possibility of an agent in the first space state is very small because the process of mutation occurs after the strategy simulation and movement. For the second type of space state, because the next game return of the mutant who changes from defector to cooperator is less than the returns of other defectors, the strategy type of the other neighbors is not affected in the next round of strategy simulation. Overall, the level of cooperation is reduced by the introduction of the small mutation rate.

Next, the effect of the value of c on the level of cooperation is analyzed. This paper discusses the range $c \in [1, 50]$ because the maximum payoff of the agent is $4b$, where $b \in (1, 2)$, and the migration mechanism is based on formula (3). Moreover, individuals cannot move when the difference between cost and payoff is too large. However, the migration mechanism still plays a role in promoting group cooperation with other values of c. The movement based on strategy maintains the small clusters of cooperators, and the migration based on smaller cost increases the possibility that cooperators will escape from defectors and expand the formation of cooperation clusters when $q = 0.0$, thus increasing the level of cooperation. Fig. 1(a) and (c) also show that the increased cost does not reduce the level of cooperation, though the time required for cooperation to reach steady state is extended with an increase in costs. There are two reasons for the above result. First, the higher cost limits the movement of cooperators and reduces the possibility of cooperators escaping from defectors, thus reducing the level of cooperation. The results are reflected in the early evolution (as shown in Fig. 1(a) and (c), $t \in [0, 2000]$). Second, analyzing from the perspective of long-term evolution, a smaller migration rate still gives cooperators a chance to escape from defectors and promotes the formation of small clusters of cooperation. Although the high cost slows the expansion speed of cooperators clumps, it also decreases the opportunity for defectors to invade cooperators. The cooperators clumps gradually expand until they stabilize through a smaller migration rate after a certain time. In other words, at a high cost, the update rate of the network topology is reduced, but the level of cooperation is not reduced. The above result is consistent with the experimental conclusion of Bednarik et al. [73]. Therefore, in the long run, the migration based on strategy and cost is effective in promoting the cooperation, even if at a high cost. Given the mutation rate $q = 0.001$, the reason for higher-level cooperation at a lower cost is similar to that with no mutation, though there are two reasons for the suppression of cooperation at a higher cost. On the one hand, the small cooperative clusters are destroyed by the mutation, leading to the collapse of small cooperative clumps. On the other hand, the higher cost reduces the possibility of cooperators escaping from defectors, thus reducing the level of cooperation. Both reasons result in the extinction of cooperation.

Fig. 5 shows the influence of the defection parameter b on the evolution of cooperation under the migration based on strategy and cost. The results show that the level of cooperation is high at a smaller value of b and decreases with the increase of b. There is a critical value of b when the level of cooperation drops to 0. This result is consistent with the studies of Liu et al. [3]. It can be observed from Fig. 5(a) that the critical value of b is 1.46 when $q = 0.0$ and $c = 1$. The level of cooperation is maintained at approximately 0.8 when $b < 1.46$, and the level of cooperation then rapidly decreases to 0 when $b > 1.46$. The critical values of $b = 1.45$, $b = 1.5$, and $b = 1.45$ are also found when $q = 0.001$ and $c = 1$, $q = 0.0$ and $c = 5$, $q = 0.001$ and $c = 5$, respectively. The larger b value increases the difference of payoff between the defector on the boundary of cooperative clusters and the cooperator belonging to the cooperative clumps, making it easier for the cooperator to imitate the defection strategy. Thereby, the formation of clump of cooperators is cut off, and the two-dimensional space is fully occupied by defectors.

Figs. 6 and 7 show the spatial patterns under different density values ρ to intuitively understand the promotion of migration based on strategy and cost on the evolution of cooperation. Specifically, Fig. 6 shows the evolutionary spatial pattern over time when $q = 0.0$, $b = 1.4$, $c = 1$. It reveals that the level of cooperation sharply decreases at

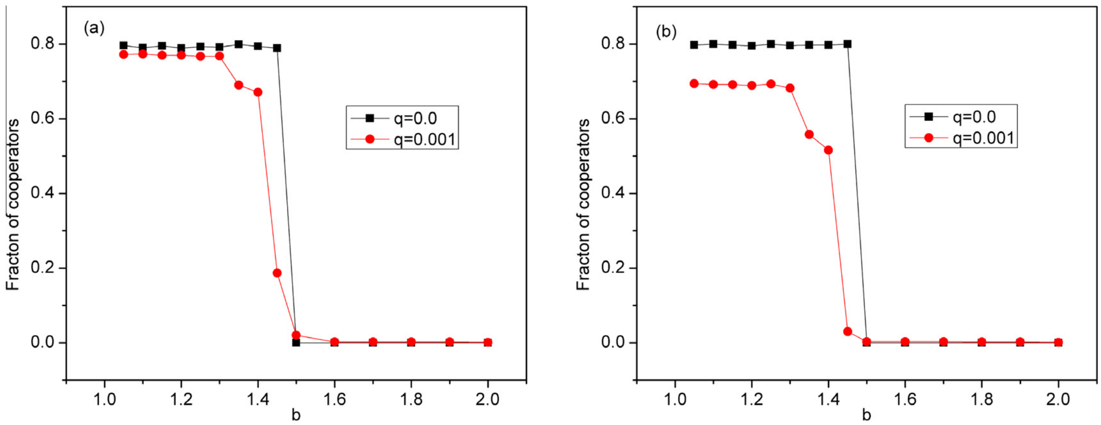

Fig. 5. Fraction of cooperators f_c as a function of defection parameter b for different mutation rate. (a) $c = 1$, (b) $c = 5$. Other parameters: $\rho = 0.625$, $d = 0.5$, $N = 1000$. The data points are obtained in the same way as in Fig. 2.

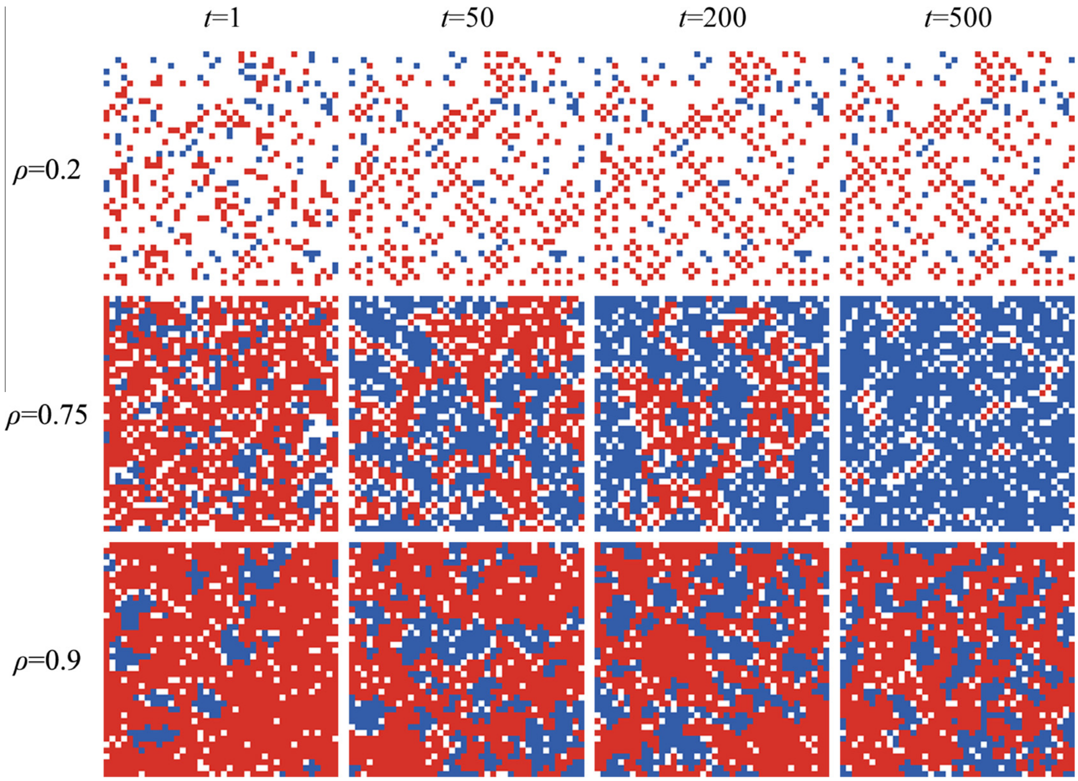

Fig. 6. Some typical snapshots for different density ρ versus time. Other parameters: $q = 0.0$, $d = 0.5$, $L = 40$, $c = 1$, $b = 1.4$. Cooperators are represented by blue patches, and defectors are represented by red patches. No agents are represented by white patches. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the beginning of evolution, independent of density. This occurs because the migration mechanism has not sufficient time to become effective and because the payoff for defectors is larger than that for cooperators, leading most of the cooperators to turn into defectors. Due to the small density value $\rho = 0.2$, too few cooperators interact with each other, and the migration mechanism based on strategy cannot promote the emergence of small cooperative clusters. Therefore, the level of cooperation cannot be improved when $\rho = 0.2$. The migration mechanism plays a significant role in improving cooperation level when $\rho = 0.75$. Small cooperative clumps emerge and expand over time until most of the cooperators occupy the spatial structure and only a few isolated defectors survive. At the moment, the

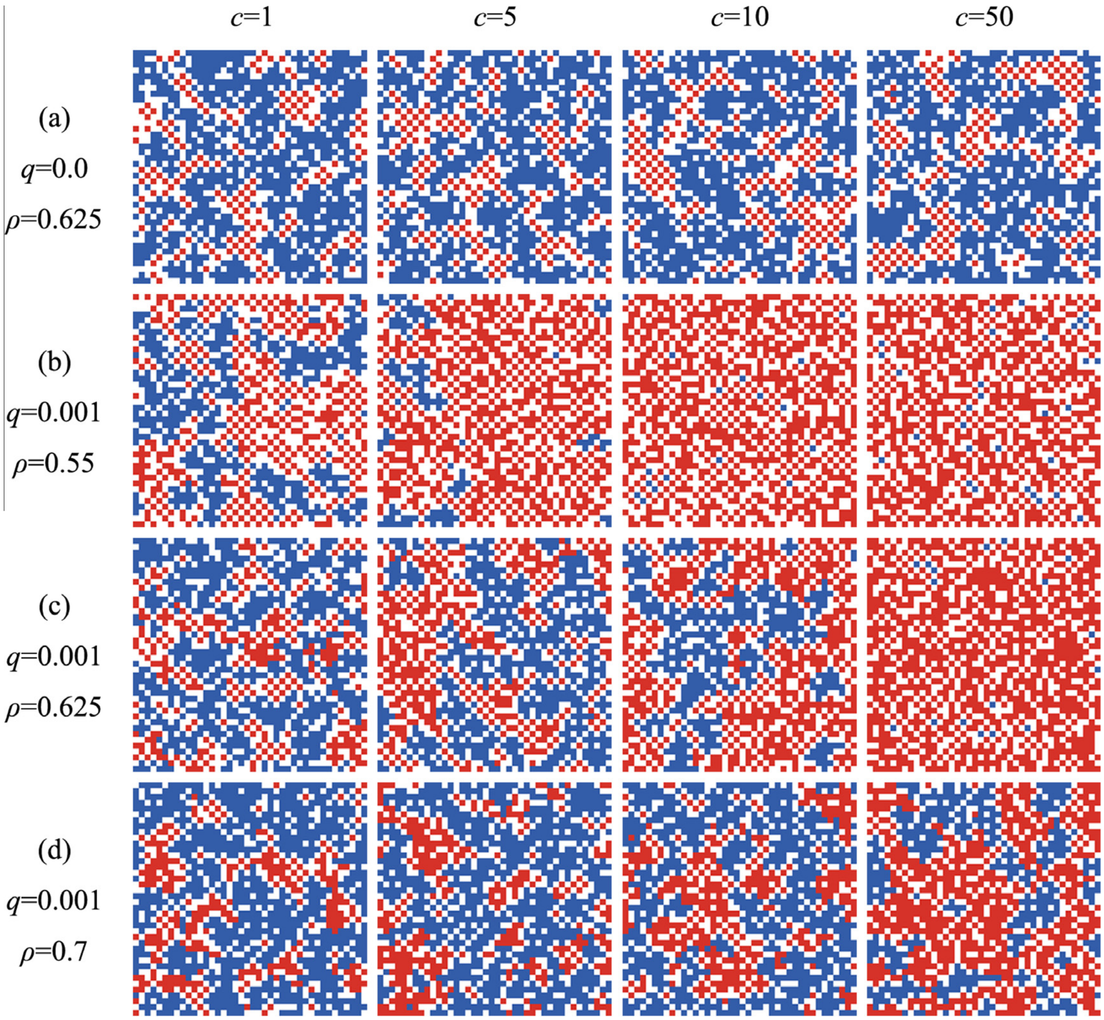

Fig. 7. Typical snapshots of the stationary distributions of cooperators and defectors for different values of c and ρ. Parameters: $d = 0.5$, $L = 40$, $b = 1.4$. Cooperators are represented by blue patches and defectors are represented by red patches. No agents are represented by white patches. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

network topology cannot be updated, and the cooperation tends to stabilize. Populations keep a lower level of cooperation when $\rho = 0.9$ because the density value is so large that there are not sufficient vacant sites for cooperators to escape from defectors, thereby reducing the possibility for the cooperative clusters to expand. A few vacant sites are beneficial for the survival of the small cooperative clumps.

Fig. 7(a) shows the spatial patterns at the steady state under different costs c when $q = 0.0$, $\rho = 0.625$, $b = 1.4$. Fig. 7(b–d) show evolutionary spatial patterns under different densities ρ and costs c when $q = 0.001$, $b = 1.4$. We can observe in Fig. 7(a) that increasing the migration cost does not have an evident effect on the level of cooperation when $q = 0.0$, which is consistent with the conclusion drawn from Fig. 4. Fig. 7(b–d) also verify the conclusion from Fig. 4 that the cooperation level is lower with an increase in migration cost and is unchanged until the cooperators are almost extinct when $q = 0.001$. Additionally, we find that the critical value of migration cost c that makes cooperators extinct is dependent on the density ρ. Under $\rho = 0.55$, some cooperators survive when $c = 5$, whereas there are almost no cooperators when $c = 10$ and $c = 50$. Under $\rho = 0.625$, a large number of cooperators remain when $c = 5$, and some cooperators can be maintained when $c = 10$, but there are hardly any cooperators when $c = 50$. Some cooperators still survive when $\rho = 0.7$ and $c = 50$.

4. Conclusions

The effect of migration based on strategy and cost on the evolution of cooperation has been discussed in the Spatial Prisoner's Dilemma Game. Furthermore, the effects of mutation rate q, migration cost c, density ρ and defection parameter b on the level of cooperation have been analyzed under this migration. Finally, the spatial state diagrams under different conditions have been shown to provide an intuitive understanding of the effects of migration on cooperation. The results show that the migration based on strategy and cost promotes the emergence of cooperative behavior and improves the level of cooperation in a wide parameter space. This is mainly caused by two reasons. On the one hand, movement based on strategy effectively promotes the emergence of cooperation clumps. On the other hand, movement based on cost effectively regulates the rate of movement. Both types of movement provide a favorable guarantee for the evolution of stable cooperation under the mutation rate $q = 0.0$.

The influence of several variables on the level of cooperation under this migration occurs primarily in the following respects:

1. The level of cooperation is weakened after the addition of mutation.
2. An optimal density value ρ resulting in the maximum level of cooperation exists with or without the mutation.
3. Increased costs have no effect on the evolution of cooperation when the mutation rate is $q = 0.0$ under a certain density. The level of cooperation decreases until it is near 0, along with the increase in cost when $q = 0.001$.
4. The level of cooperation is high when the value of b is less than the critical value. The level of cooperation is collapsed when the value of b is greater than the critical value.

In addition, we conduct robust tests on the parameters to ensure the stability of the conclusion in our context. In the migration based on strategy and cost, the agents consider not only their own ability but also the environment around them, which provides an effective way for understanding the emergence of cooperation in our society.

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