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Effect of self-interaction on the evolution of cooperation in complex topologies

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HIGHLIGHTS

- A new self-interaction mechanism in the prisoner's dilemma and the snowdrift games is proposed.
- The evolution of cooperation is elevated to a very high level.
- The promoting effects are independent of the structure of the applied spatial networks and the potential evolutionary games.

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ABSTRACT

Self-interaction, as a significant mechanism explaining the evolution of cooperation, has attracted great attention both theoretically and experimentally. In this text, we consider a new self-interaction mechanism in the two typical pairwise models including the prisoner's dilemma and the snowdrift games, where the cooperative agents will gain extra bonus for their selfless behavior. We find that under the mechanism the collective cooperation is elevated to a very high level especially after adopting the finite population analogue of replicator dynamics for evolution. The robustness of the new mechanism is tested for different complex topologies for the prisoner's dilemma game. All the presented results demonstrate that the enhancement effects are independent of the structure of the applied spatial networks and the potential evolutionary games, and thus showing a high degree of universality. Our conclusions might shed light on the understanding of the evolution of cooperation in the real world.

1. Introduction

Cooperative behavior is abundant in biological and social systems, ranging from microorganism groups to complex human societies [1–6]. Yet, cooperation is not the best strategy for an individual according to Darwin's theory of evolution [7–9]. Thus, how to explain the emergence and persistence of cooperation in the real world has become a thorny subject among research enthusiasts [10,11]. The evolutionary game theory is often used as a unified mathematical framework to study the evolutionary dynamics of cooperative behavior traits, in which social contradictions are analogous to the competition between peers (cooperators or defectors) for limited resources [12–16].

Among the frameworks of evolutionary game theory, two classical models for pairwise interactions, the prisoner's dilemma game (PDG) and the snowdrift game (SDG), are often adopted to explore the evolution of cooperation [17–20]. In the traditional mathematical formulation of PDG with pairwise interaction, the cooperator gets a payoff R (S) if confronting

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a cooperator (defector), while the defector gains T (P) when encountering a cooperator (defector). These parameters are supposed to ensure a proper payoff ranking ($T > R > P > S$), which captures the essential social dilemma between the individual and the common interests. Players in the SDG interact in a similar way, and what is different from the PDG is that the payoff P for mutual defection is less than the so-called sucker's payoff S. This means that payoffs satisfy the ranking $T > R > S > P$ in the SDG. According to the payoff ranking, evidently, defection is unbeatable and thus preferred by rational players for the one-shot PDG, although they may be aware of that mutual cooperation yields higher payoff for the whole group than mutual defection [21,22].

However, the unfavorable equilibrium behavior (defection) predicted in the traditional PDG is often contradictory in the real world [23–28]. To understand the origin and evolution of cooperation in nature, various typical mechanisms including memory effect [29–31], reward [32–36], punishment [37,38], personal reputation [39,40], and different update rules [41–43] are proposed. All the mechanisms are attributed by Nowak to the following five scenarios: kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection [44]. Among these mechanisms, network reciprocity becomes the focus of numerous cross disciplines [45–51]. This is because the agents especially the cooperators located on the spatially structured topologies can survive by forming compact clusters to resist the aggression of defectors and protect those cooperators who are situated in the interior of the clusters [19,52]. Therefore, the evolutionary games on complex networks are favored by people all over the world [53–55]. In particular, no one is isolated in the real world. On the contrary, all the members in society can be directly or indirectly related, which is similar to the vertices to some degree in the connected graph.

In this work, we wish to extend the scope of evolutionary games on complex networks. In the most previous works, the impacts of the agent's own strategy on its payoff have not attracted enough attention. In most previous work, the focal player is assumed to play the game only with its nearest neighbors. If the focal agent plays the game not only with its nearest neighbors but also with itself, the cooperator will obtain an additional income R according to the payoff matrix. In order to explore the impact of self-interaction on the evolution of cooperation more comprehensively, the additional reward can be extended to values other than R. In a recent paper, the role of self-interaction is taken into consideration, where the authors consider the additional benefit for both the fixed and the random cases [56,57]. Here, the extra bonus for the cooperator is considered as a special way of reward, therefore, the self-interaction is treated as a social reward as well. As expected, cooperation is elevated to a higher level under this mechanism. However, the only thing missing there seems to be lack of universality for different topological structures. Besides, the influence of update rule on the evolution of cooperation also slips through the net under this mechanism. Therefore, we will further address the impact of self-interaction on cooperation behavior under different topology structures and with a different upstate rules with the reference [56]. Both the fixed and the random additional benefits are considered in the models. The simulation results will further broaden our horizons about the effect of reward on the evolution of cooperative behavior among unrelated individuals in the spatial PDG and SDG models.

The remainder of this work is structured as follows. In Section 2, we describe the game model in detail. And then, numerous simulation results are presented in Section 3 to discuss the effect of self-interaction in promoting cooperation. Finally, we summarize our conclusions in Section 4.

2. Evolution game model and dynamics

Here, we consider an evolutionary prisoner's dilemma game, in which the agents occupy the vertices of the discussed networks. Each player is initially designated either as a cooperator or a defector with equal probability. The evolutionary PDG is characterized with the temptation to defect $T = b$, the reward for mutual cooperation $R = 1$ and the punishment for mutual defection $P = 0$ and the sucker's payoff $S = 0$. In principle, according to the payoff ranking, the sucker's payoff S should be smaller than P. While it is interested to note that the results are robust and can be observed in the full parameterized space even in the weak version (namely, $S = 0$). For the SDG, it is characterized with the ratio of cost to benefit r ($0 < r < 1$). During the SDG process, the temptation to defection T equals $1 + r$, the reward for mutual cooperation $R = 1$, the punishment for mutual defection $P = 0$, and the payoff for the cooperator confronting a defector $S = 1 - r$.

In this work, we introduce self-interaction in the 2-person evolutionary games (PDG and SDG). In the model, a cooperator will obtain a fixed reward γ ($0 \le \gamma \le 0.1$), or a random reward γ within the interval [0, c], where c is some parameter less than or equal to 0.1. While if the player chooses to defect, it will gain no additional benefit. For further testing the robustness of the impact of this newly introduced mechanism on the evolution of cooperation, different networks topologies including regular square lattice, Erdös–Rényi (ER) random graphs and Barabási–Albert (BA) scale-free (SF) networks are taken into consideration.

The simulation is conducted in accordance with the Monte Carlo simulation procedure comprising the following elementary steps. Firstly, a random selected player x plays the game with all its nearest neighbors and acquires its payoff P_x by adding all the obtained payoffs. Then, all the agents synchronously update their strategy by choosing one of their neighbors randomly, say y, and comparing the respective payoffs P_x and P_y. Unlike Ref. [56], we adopt the replicator dynamics to replace the Fermi-like rule as the evolutionary dynamics. If $P_x > P_y$, agent x will maintain its strategy for the next step. Otherwise, player x will copy the strategy of the selected neighbor y with a probability proportional to the payoff difference:

$$W_{x \longrightarrow y} = \frac{P_y - P_x}{\max\{k_x, k_y\} D}, \tag{1}$$

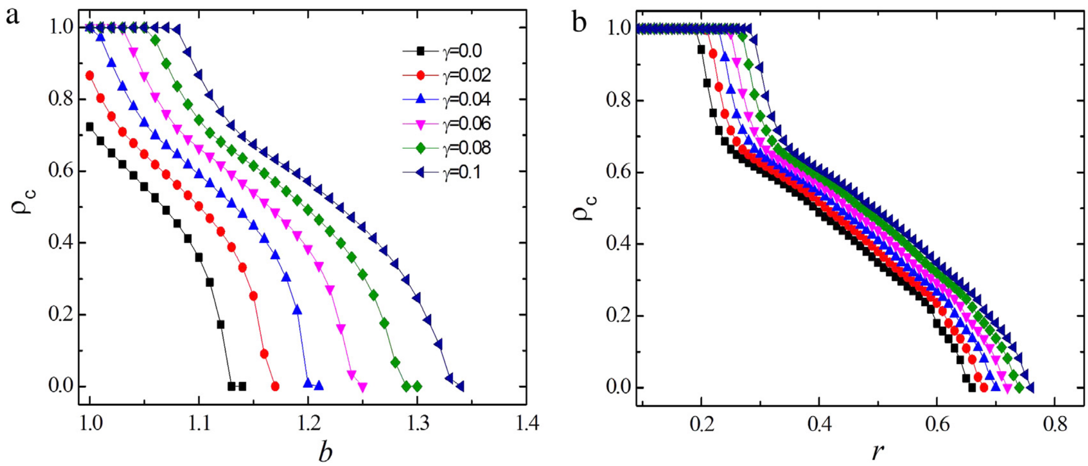

Fig. 1. Fraction of cooperators (ρ_c) in the PDG (panel (a)) and the SDG (panel (b)) under different fixed self-interaction strength γ. All the results are obtained in the von Neumann neighborhood in square lattice for $N = 10^4$ nodes, MCS=60,000 and $\langle k \rangle = 4$.

where k_x and k_y represent the degrees of players x and y, respectively, and D denotes the maximum possible payoff difference between the two agents. It is noted that each player has a chance to adopt one of their neighbors' strategies once on average during one full Monte Carlo simulation (MCS). Finally, if the aforementioned two steps are completed, a full Monte Carlo step will be finished. After a period of evolution, the system finally reaches the equilibrium state.

In the following simulations, all the considered networks are set at the same size ($N = 10^4$ nodes) and the same average degree, i.e., $\langle k \rangle = 4$. Each independent run will last 60,000 MCS steps and the fraction of cooperators (ρ_c) will be obtained by averaging the last 4000 MCS steps. Moreover, all the simulations are averaged over 40 independent rounds.

3. Results and analysis

We firstly consider the case of fixed reward for self-interaction in the PDG and the SDG on the square lattice with periodic boundary conditions. Each player plays the game with the four nearest neighbors (von Neumann neighborhood) and a additional bonus γ will be accumulated if the focal player chooses cooperation strategy during the game. The fractions of cooperators (ρ_c) at the stationary state as a function of temptation to defect b are shown in Fig. 1. The results of panel (a) and panel (b) represent the evolutionary PDG and SDG models, respectively. It is clearly indicated that the evolution of cooperation is greatly promoted under the newly introduced mechanism. When γ equals to 0.0, our models collapse into the traditional versions and no extra bonus is awarded to the cooperative agents, and the evolution of the cooperation is entirely sustained by network reciprocity. In this case, the cooperators die out soon with the increase of b (approximately equal to 1.13). When the self-interaction is considered, the critical values (b_c) where the extinction of cooperation strategies occur gradually shift right with the increase of γ as shown in Fig. 1(a). It is easy to understand the enhancement of the evolution of cooperation. The additional positive award for the cooperators raise the cooperators' payoffs and then reinforce the advantages of the cooperation strategy during the strategy spread, which makes the agents prefer cooperating to defecting. Catalyzed by network reciprocity, those agents who choose to cooperate can resist the invasion of the defectors by forming large compact cooperative clusters. However, when the temptation to defect b continues to rise, the cooperators located on the edge of the cooperative clusters are prone to exploitation by defectors, which eventually leads to the dissolution of cooperative clusters.

The simulation results are qualitatively consistent with the conclusions reported in Refs. [56] and [58]. However, it is interesting to note that compared with the results in which the system proceeds in accordance with a Fermi-like rule in Refs. [56] and [58], the enhancement of cooperation becomes more obvious with replicator dynamics. As an example, for the case of $\gamma = 0.1$, the critical value of b - b critical — above which cooperators die out shifts right in this work compared with the reported results in Refs. [56] and [58], which implies the superiority of the replicate dynamics. Moreover, it is not difficult to predict that if we fix $\gamma = 1.0$ just as the references do, it will enhance the evolution of cooperation to a higher degree. As expected, the self-interaction in the SDG also plays a strong role in promoting the evolution of cooperation as illustrated in Fig. 1(b). The simulation results of the PDG and the SDG may suggest that the self-interaction is generally valid in promoting the evolution of cooperation, irrespective of the potential evolutionary games.

Going further in the exploration of robustness of our findings, we conduct the evolutionary PDG on the Erdös–Rényi (ER) graph and the Barabási–Albert (BA) scale-free (SF) network topologies. The Monte Carlo results for the concentration (fraction) of cooperators (ρ_c) versus b are presented in Fig. 2(a) and Fig. 2(b), which correspond to the ER and the BA network topologies, respectively. Compared to the traditional version marked in black dot line, the fraction of cooperators is clearly enhanced. As an example, when $\gamma = 0.1$, the critical value b_c almost shifts to 2.0, implying that the cooperators can survive

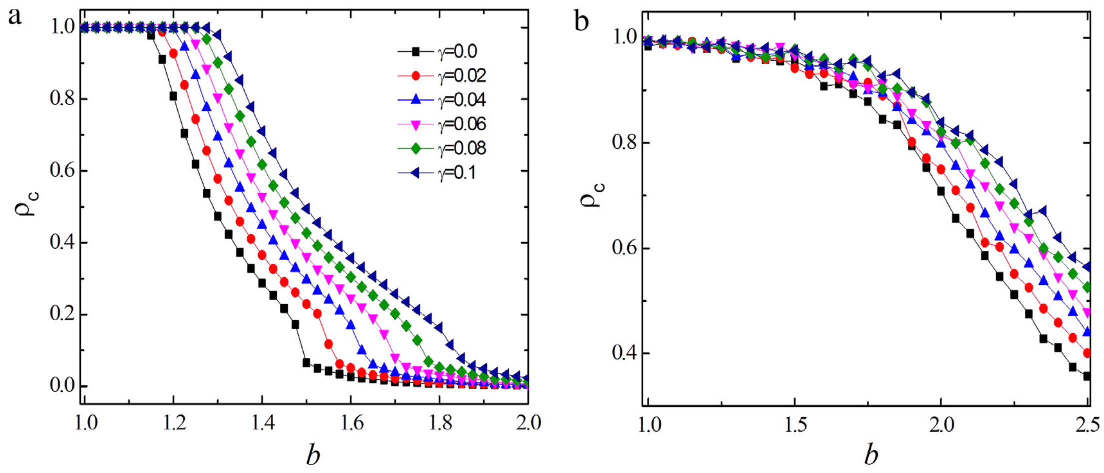

Fig. 2. Fraction of cooperators (ρ_c) in the PDG under different fixed self-interaction strength γ as a function of the temptation to defect b. The networks in panel (a) and panel (b) are an ER graph and a SF network, respectively. The other parameters are consistent with Fig. 1.

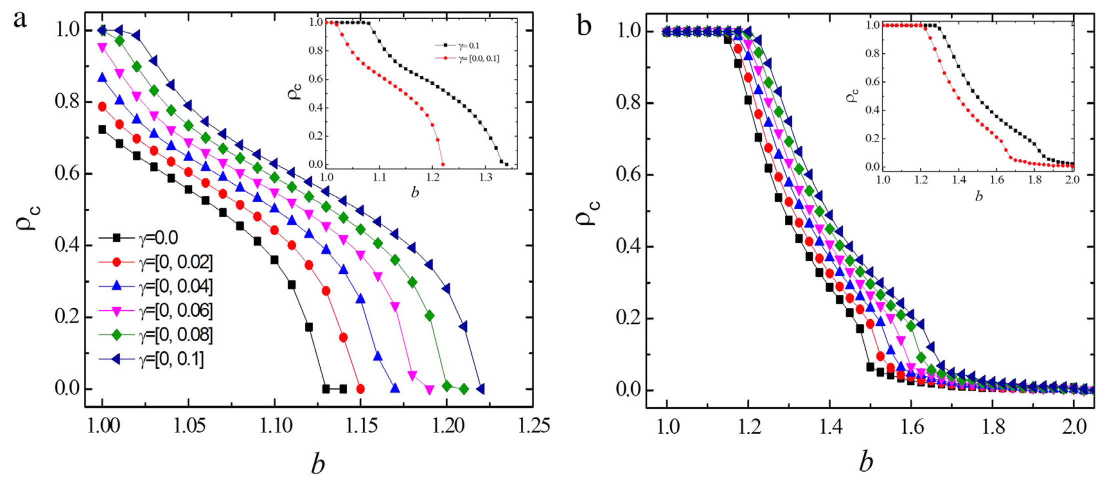

Fig. 3. Fraction of cooperators (ρ_c) in the PDG under the random self-interaction strength γ as a function of the temptation to defect b. The self-interaction strength γ is fixed to be 0 and distributed within the interval [0, 0.02], [0, 0.04], [0, 0.06], [0, 0.08] and [0, 0.1], respectively. The networks in panel (a) and panel (b) are an ER graph and a SF network, respectively. The insets of the two panels display the comparison between the fixed self-interaction strength and the random self-interaction strength. All the results are obtained in the von Neumann neighborhood for $N = 10^4$ nodes, MCS=60,000 and $\langle k \rangle = 4$.

or even thrive within a large range of b values. The change trends of the fraction of cooperators versus γ are similar to the findings discussed above for the square lattice, in which the concentration of cooperators and the intensity of self-interaction are positively correlated. The results in homogeneous graphs and heterogeneous networks show that the self-interaction mechanism discussed here can be beneficial for sustaining cooperative behavior independent of the structure of the applied interaction networks and the studied social dilemma games, and thus appears to have a high degree of generality.

To have further information about the role of the self-interaction, we relax the condition of fixed self-interaction strength and make a thorough inquiry in the impact of random self-interaction strength on the evolution of cooperation. The PDG, served as the paradigm for expressing social dilemma in the case of pairwise interactions, is still selected as the basic model for the evolutionary game in this part. The agents who choose cooperation strategy can obtain a random additional benefit γ (a uniformly distributed random number between 0 and c). The fractions of the cooperators ρ_c as a function of the temptation to defect b at the equilibrium state are displayed in Fig. 3, in which Panel (a) and panel (b) represent the results in square lattice and the ER network topologies, respectively. Remarkable enhancement of the cooperation is observed in the both graphs. Under the same b value, the fraction of the cooperators is directly proportional to the intensity of self-interaction (marked with γ), which is consistent with the case of fixed reward discussed above. However, the effects of promoting the evolution of cooperation for the two cases are not exactly the same. For instance, the insets of the two panels display the comparison between the fixed and the random reward, in which the fixed reward value γ equals the available maximum value in the random case. In the two comparative treatments, the fixed reward has the upper hand, as expected. This is easy to

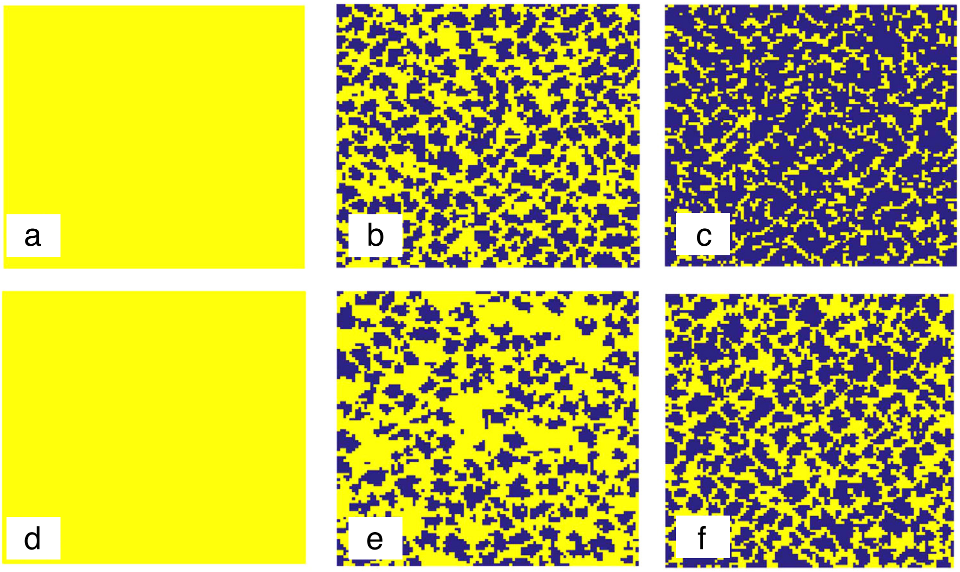

Fig. 4. Snapshots of the distribution of cooperators (dark blue) and defectors (yellow) at the final time step (MCS = 60,000) under the self-interaction mechanism in the PDG. In the top three panels [from panel (a) to (c)], the self-interaction strength is assumed to be 0, 0.04 and 0.1. While for the bottom panels, the self-interaction strength is 0 [panel (d)] or taken from [0, 0.04] [panel (e)] or [0, 0.1] [panel (f)]. The temptation to defect b is fixed to be 1.13 in all the figures. The other parameters are the same as in Fig. 3. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

understand, because the agents in the fixed reward case have a hundred percent probability to obtain the additional benefit $\gamma = 0.1$, while the players in the random reward case have a lower probability to get the maximum reward ($\gamma = 0.1$). It is testified from the side that the evolution of the cooperation is positively dependent on the self-interaction intensity.

Subsequently, it is interesting to analyze the characteristic snapshots of the distribution of cooperators and defectors on the square lattice for different values of γ. The simulation results are presented in Fig. 4 (yellow and dark blue represent the defectors and the cooperators, respectively), in which the temptation to defect b is fixed to be 1.13 and the self-interaction strength is set to be 0, 0.04 and 0.1 from panel (a) to panel (b). For $\gamma = 0$, the model is reduced to the traditional version and the applied temptation value does not sustain cooperation. The cooperative clusters cannot be effectively organized so that the cooperators eventually die out, as shown in panel (a). When the value of γ increases ($\gamma = 0.04$), the situation is improved. As illustrated in panel (b), numerous cooperators survive at the final time step (after 10^5 MCS). Meanwhile, if γ is increased up to 0.1, it can be observed from panel (c) that the cooperators form a giant clusters surrounding some tiny surviving defectors clusters. The simulated phenomenon imply that the cooperators can survive or even thrive owing to the introduction of self-interaction. The figures in the bottom panels (from panel (d) to panel (f)) represent the conditions in random reward, in which the self-interaction strength is taken from 0.0 to the possible maximum reward γ corresponding to 0.0, 0.04 and 0.1, respectively. As expected, the evolution of cooperation is enhanced just as the case of fixed self-interaction strength. In particular, the wider the interval is distributed, the more obvious the promoting effect is. It is not difficult to speculate that if γ continues to rise, the cooperators will eventually occupy the whole population. The numerical simulations indicate that the promotion of cooperation can be very noticeable whether in the case of fixed self-interaction strength or in the case of random self-interaction strength. However, as b continues to increase, the defectors begin to invade the cooperator clusters until it splits in small parts and the defectors finally occupy an absolute competitive advantage.

To get more clear analysis for exploring the essence of this boosting effect, we record the temporal traits of the fraction of cooperation ρ_c for different values of the selection parameter γ in Fig. 5. The fixed and random reward evolutionary scenarios are illustrated nicely in panel (a) and panel (b), respectively. The temptation to defect b is fixed to be 1.15 in the both scenarios. The values of γ in the fixed self-interaction strength and the available maximum values under the random self-interaction strength are set to be 0.0, 0.04 and 0.1 as shown in the figures. It can be clearly observed that the performance of defectors is better than that of cooperators in the early stages of the evolutionary process, irrespective of the γ values. Actually, this is in line with what one would expect that defectors are more successful than cooperators and thus be chosen likely as potential strategy donors given that in mixed environment. For $\gamma = 0$ (namely, the traditional version), the decimation of cooperators cannot cease and the cooperative agents die out soon. However, the cooperators may win the advantages over defectors after this stage when the self-interaction is taken into consideration. As γ increases ($\gamma = 0.04$), it can be observed that the invasion of defectors is effectively restrained and the evolution of cooperation has been widely disseminated. Obviously, the reversal of cooperation is positively related to the value of γ. For large γ ($\gamma = 0.1$), the final fraction of cooperators reaches a higher level (approximately equal to 0.70). It is not difficult to predict that the

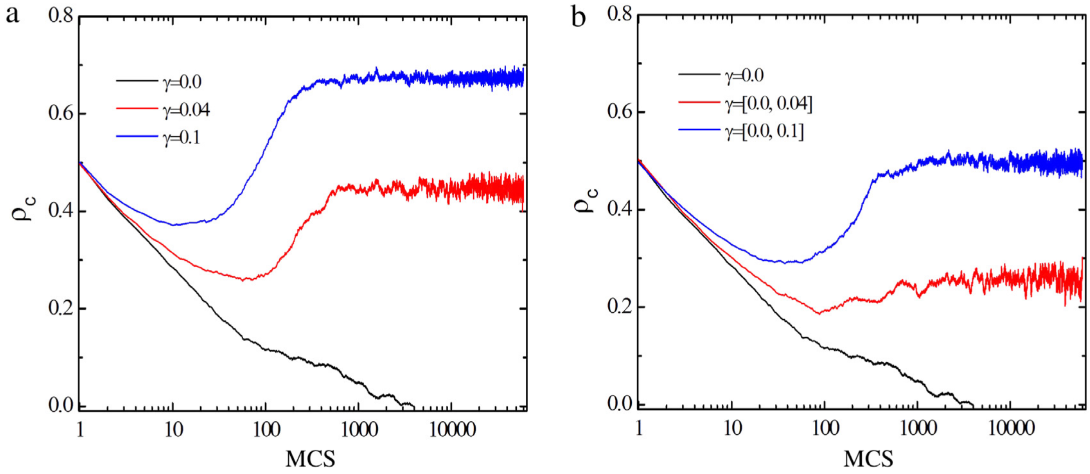

Fig. 5. Time courses of the fraction of cooperators ρ_c in the PDG on a square lattice. In panel (a), the self-interaction strength γ is assumed to be 0, 0.04 and 0.1. While in panel (b),the self-interaction strength γ is 0 or taken from [0, 0.04] or [0, 0.1]. All the results are obtained for $b = 1.15$, $N = 10^4$ nodes, MCS=60,000 and $\langle k \rangle = 4$.

final equilibrium fraction of cooperators ρ_c will continue to increase till up to 100% with the continuous increment of γ. The cooperation can be sustained through the self-interaction, since the choice of cooperation strategy can make the individual get additional benefits. Based on these findings, we draw a conclusion that the introduction of self-interaction accelerates the microscopic dynamics of cooperator clusters and promotes the evolution of cooperation. Moreover, these promoting effects are valid for both fixed and random self-interaction strengths as depicted in the figures, which are consistent with the aforementioned results.

4. Conclusion

In summary, we have studied the influence of the introduction of self-interaction on the evolution of cooperation in the prisoner's dilemma game and the snowdrift game. The games are conducted in the square lattice with periodic boundary conditions, ER graphs and BA topologies. It is found that the evolution of cooperation has been greatly improved for both the cases of fixed and random self-interaction, which is independent of the underlying evolutionary games and potential interaction network. The numerical simulation results testify that this promotion effect is universal. Moreover, to explore the mechanisms that drive the survival of cooperative behavior, we inspect the characteristic spatial configuration of the agents for different values of γ. Through analysis, the promoting effect of the mechanism can be attributed to the formation of compact cooperative clusters. Obviously, enhancing the value of γ can help to favor the microscopic organization of the cooperator clusters, which makes the cooperators impervious to defector invasion even at a high temptation to defect b. In addition, the time courses of the fraction of cooperation ρ_c under different self-interaction intensity γ are presented as well. With regard to these observations, we hope that this work can be beneficial for us to further resolve the social dilemmas, especially in the realistic scene.

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