Adaptive persistence based on environment comparison enhances cooperation in evolutionary games

Liming Zhang, Haihong Li, Qionglin Dai*, Junzhong Yang

School of Science, Beijing University of Posts and Telecommunications, Beijing 100876, China

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ABSTRACT

Switching strategy is generally accompanied by material cost or mental pressure to players in reality. An efficient solution is to hold the current strategy for a period time before the next updating. In evolutionary games, it has been reported that strategy persistence or strategy inertia could promote cooperation. There arises a question that how players determine the duration of their strategy persistence time, which is also called the persistence level. Here, we consider the evolutionary prisoner's dilemma games in which players can adapt their persistence levels based on the comparison between the local and global environments. We assume that, the players who have better local environments tend to preserve their current strategies longer and increase the persistence levels. In contrast, those whose local environments are worse than the global environment tend to decrease their persistence levels. The results show that network reciprocity can get greatly enhanced by such an adaptive strategy persistence, especially in hostile environments to cooperation. Moreover, by comparing with the fixed and randomly adaptive persistence level cases, we emphasize the importance of the environment comparison in enlarging the persistence levels of cooperators, which could be further enhanced by a larger upper limit or a smaller increment of persistence level. Our results provide insights into the promotion of cooperation by the adaptive strategy persistence when players can perceive both the local and global environments in evolutionary games.

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1. Introduction

Darwin's theory predicts that natural selection favors the selfish and strong [1], in which case the cooperators who sacrifice their own interests to benefit others are hard to survive. However, altruistic cooperation is ubiquitous both in animal species and human beings [2–4]. To explain the evolution of cooperation, researchers from various fields have put much effort into understanding the emergence and maintenance of cooperation [5–9]. Evolutionary game theory [10,11] has been intensively applied to such problems as an important theoretical framework, especially for the situations where conflicts between individual and collective interests exist, the so-called *social dilemma*.

The 2-player-2-strategy (2 × 2) game [12,13] is one of the most important and fundamental paradigms used in evolutionary games, which could portray various scenes of pairwise interactions. In a 2 × 2 game, players can choose one strategy from two options, *cooperation* (C) and *defection* (D). They gain equal payoff R for mutual cooperation or P for mutual defection. If two players hold different strategies, the cooperative one gains S and his defective opponent gains T. By varying the

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* Corresponding author.
E-mail address: qldai@bupt.edu.cn (Q. Dai).

payoff parameters, this game model is able to describe a wide range scenarios of social dilemmas. The prisoner's dilemma game (PDG) ($T > R > P > S$ and $T + S < 2R$) therein has attracted most concern. It captures the most common case in real life that to defect or to be a free-rider is more profitable for an individual, though mutual cooperation can obtain the best collective interests. The early PDG-based studies have focused on well-mixed groups [14–16], where individuals interact with others by randomly matching or in a full-connected population. Under these situations, cooperation cannot emerge or maintain. In realistic cases, however, the population are structured and players usually interact with same encounters repeatedly who are only a subset of the whole population. Therefore, the population are naturally modeled by complex networks, where the vertices represent the individuals and the edges limit the interaction ranges. In structured population, cooperators might be survived in social dilemmas by forming clusters, which is known as network reciprocity [17–21]. Meanwhile, numerous fundamental mechanisms that explain the evolution of cooperation have been revealed during the past few decades, including reputation [22–27], migration [9,28–30], conformity [31–34] and punishment [35–37].

In reality, making changes in pursuit of high returns often comes with risks and direct costs [38–40], including the cost of strategy change proposed in Ref. [39] and the "stubbornness" advanced by Ref. [40]. In addition, inertia was also introduced in decision making and strategy updating in Ref. [41] as a form of hindering too fast strategy switching. They found the dilemma situation can be alleviated or even entirely removed. The authors in Ref. [42] considered another case that players would keep their strategies for a fixed period of time τ to avoid such cost. They found the strategy-persistence mechanism can enhance cooperation level of the population regardless of the underlying network structures. Afterwards, they further investigated the question that who should be more persistence in order to improve cooperation level [43]. By comparing four different distributions of P-individuals with nonzero strategy persistence level, they found cooperation could be improved if the P-individuals are played by the leaders with high degrees in the population. Besides, "zealot cooperators" who always cooperate in dilemma situations irrespective of the result of an interaction may trigger an explosive of cooperation in well-mixed populations [44] while destroy cooperation in regular population structures [45].

For population with heterogenous personalities [46–48], the attribute of strategy persistence may also vary from individuals to individuals. Moreover, the strategy persistence levels of the individuals may also evolve with their strategies during the evolution dynamics. Considering this, the authors in Ref. [49] introduced a coevolutionary framework by allowing the players to adjust their strategy persistence levels based on the comparison between the actual and expected payoffs. They found that moderate aspiration level could boost optimal cooperation level, under which the cooperators get more persistent once they cluster together and then protect them from the invasions of defectors. Apart from inner personal aspirations, the external environment can be another important factor that affects individuals' behaviors and has been considered in evolutionary games in different ways. For example, in Ref. [50], defectors in the neighbourhood are regarded as a potential danger of the immediate environment, driving players to migrate away from their original places. Along this line, the authors found that cooperation outbreaks and reaches an optimal at appropriate population densities. Recently, the authors in Ref. [51] have developed an 'eco-evolutionary game' framework in which the environmental state, governed by intrinsic growth, decay or tipping points, is introduced as the feedbacks to influence strategic interactions. Inspired by these, we propose the evolutionary PDGs by assuming that the strategy persistence levels are adaptive based on the comparison between the local and global environments. Specifically, the players whose local environment performs better than the global one are more inclined to preserve their current strategies longer, and thus they will increase their strategy persistence levels. Otherwise, they will shorten their persistence time. We carry out the numerical simulations on complex networks and focus on how this adaptive strategy persistence affects cooperation. We also compare the results with the cases of fixed and randomly changed strategy persistence levels, and show the advantages of such an adaptive mechanism in promoting cooperation.

The rest of this paper is organized as follows. In Section 2, we present the detailed model in which the adaptive strategy persistence based on environment comparison is involved in. Then, in Section 3, we show numerical simulation results and discussions. Finally, we summarize the main findings and present the conclusion.

2. Model

We consider a population placed on a $L \times L$ square lattice with periodic boundary conditions. We assume that all players in the population have the attribute of preserving strategy for a period of time. For each player i, his strategy persistence level at time t described by $\tau_i(t)$ can be changed over time. By setting $s_i(t) = 1$ when i is a cooperator or $s_i(t) = 0$ when i is a defector, we define the local environment of player i as $\varphi_i(t) = \frac{1}{k_i} \sum_{j \in \Omega_i} s_j(t)$ where Ω_i represents the set of immediate neighbors of i and k_i is the degree of i. Meanwhile, we describe the global environment by $\phi(t) = \frac{1}{N} \sum_{j=1}^{N} s_j(t)$, which is uniform for all the players at time step t.

For each player i, he firstly compares $\varphi_i(t)$ with $\phi(t)$. If $\varphi_i(t) > \phi(t)$, player i perceives his surroundings to be more rewarding than other locations, and then, he tend to increases his strategy persistence level $\tau_i(t)$. Otherwise, player i prefers to decreases $\tau_i(t)$. We use $\Delta \tau$ to control the adjustment of persistence level in one time step. Here, we adopt Fermi-Dirac function to characterize such tendency. That is, i increases $\tau_i(t)$ with the probability

$$\Gamma_i(t) = \frac{1}{1 + \exp[-(\varphi_i(t) - \phi(t))/K_1]}, \tag{1}$$
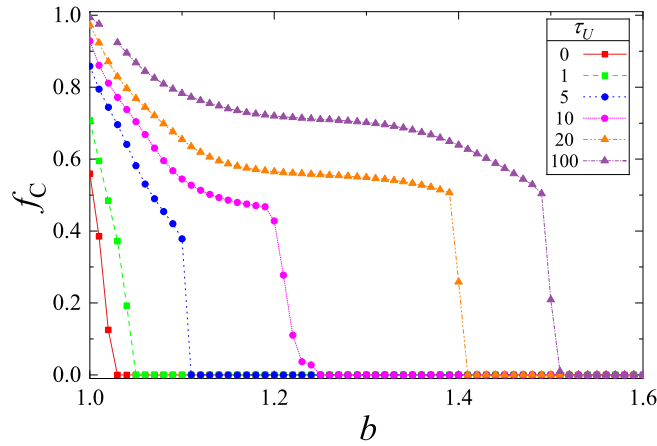
Fig. 1. (Color online) The fraction of cooperators f_C in dependence on the game parameter b for different τ_U. Other parameters: $\Delta\tau = 1$, $K_1 = K_2 = 0.1$.

and decreases $\tau_i(t)$ with the probability $1 - \Gamma$ accordingly. K_1 is the measure of stochastic noise allowing the irrational choices. For the $K_1 \to 0$ limit, $\tau_i(t)$ is increased if and only if $\varphi_i(t) > \phi_i(t)$, otherwise it is decreased. Contrarily, if K_1 is extremely large, $\tau_i(t)$ changes randomly and the environments make no difference to i's choice. In this work, we assume that the strategy persistence levels of players are in the range $[\tau_D, \tau_U]$. τ_D is fixed to zero, at which the players alter their strategies immediately. τ_U is a tunable parameter controlling the upper limit. In addition, we allocate a timer ℓ_i for each player i to record the time steps that i has been preserving his current strategy. Particularly, i will not consider updating strategies in case of $\ell_i < \tau_i(t)$. If $\ell_i \geq \tau_i(t)$, i randomly selects a neighbour j and then imitates $s_j(t)$ with the probability

$$W_{s_i(t) \leftarrow s_j(t)}(t) = \frac{1}{1 + \exp[-(\pi_j(t) - \pi_i(t))/K_2]}, \tag{2}$$

where $\pi_i(t)$ and $\pi_j(t)$ are the cumulative payoffs acquired from playing PDGs with all their neighbours, respectively. For simplicity, we set $T = b$, $R = 1$, $P = S = 0$. Similar to K_1, K_2 here characterizes the noise intensity related to the strategy adoption. Once the strategy imitation happens, we reset ℓ_i to zero. Otherwise, i keeps his strategy for one more step and thus ℓ_i is added by one.

We simulate the model by the standard Monte Carlo simulation procedure. Initially, the two strategies of C and D are randomly distributed among the players with equal probability. For each player, $\tau_i(0)$ and ℓ_i are initialized to be 0. In one Monte Carlo step, all the players update their strategy persistence levels and strategies synchronously. We focus on the co-operation level of the population in the steady states, which is measured by the fraction of cooperators f_C. For brevity, we define $\Delta E_i(t) = \varphi_i(t) - \phi(t)$ to describe the comparison results between $\varphi_i(t)$ and $\phi(t)$ during the evolution. Unless otherwise stated, the simulations are carried out in a system with $L = 100$. The results are averaged over 1000 Monte Carlo steps in the steady states after sufficiently long transient time and each data point is obtained by averaging at least 50 independent realizations. In addition, we also implement our model on Erdös-Rényi (ER) [52] and BA scale-free (SF) [53] networks, respectively, to check the robustness of the results against network topology.

3. Results and discussion

We start from the fraction of cooperators f_C against the temptation parameter b at several different τ_U, which controls the upper limit of players' strategy persistence levels. In Fig. 1, we set $K_1 = 0.1$, so that the difference between the local and global environments can be well considered by the players. As a result, the individuals with greater τ_U may accumulate higher strategy persistence levels during $\Delta E(t) > 0$, which provides a greater buffer for players to keep positive strategy persistence ($\tau > 0$) even though $\Delta E(t)$ transitorily lower than zero. If $\tau_U = 0$, the model reduces to the traditional case where the players attempt to imitate strategy at every time step [54]. From Fig. 1, it can be observed that f_C always monotonically decreases as b increases. For the traditional case in the absence of strategy persistence ($\tau_U = 0$), f_C maintains slightly higher than 0.5 at $b = 1$ but rapidly declines once $b > 1$ and drops to zero at around $b = 1.04$. By contrast, in case $\tau_U > 0$, f_C rises as a whole with the increase of τ_U. Besides, cooperation can be maintained at a high level even at very large b, and the critical values of b for the survival of cooperation are extended significantly. The results suggest that the adaptive strategy persistence based on environment comparison can greatly promote cooperation.

For a better understanding of the effects of τ_U on the strategy persistence levels for cooperators and defectors, we investigate the stationary distributions of the normalized persistence levels $\tilde{\tau}$ which is defined by $\tilde{\tau} = \tau/\tau_U$ for cooperators and defectors, respectively. The results for different values of τ_U are shown in Fig. 2. One can see that, the distributions of $\tilde{\tau}$ for defectors exceed those for cooperators in the low-persistence range, whereas things are inverse in the high-persistence
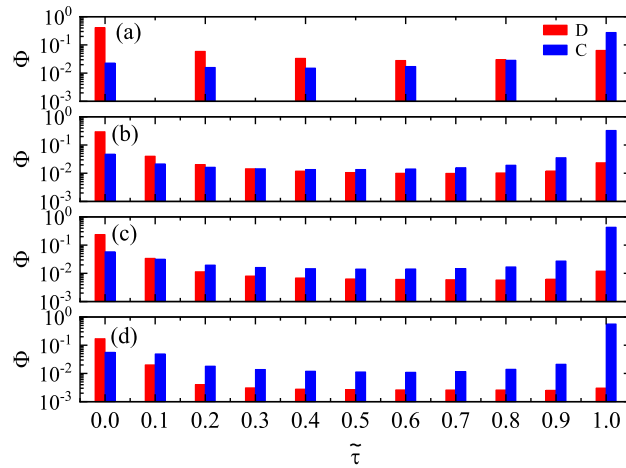
Fig. 2. The stationary distributions of the normalized strategy persistence levels $\tilde{\tau}$ for cooperators (blue) and defectors (red) at different τ_U. (a) $\tau_U = 5$, (b) $\tau_U = 10$, (c) $\tau_U = 20$, (d) $\tau_U = 100$. Other parameters: $b = 1.1$, $\Delta\tau = 1$ and $K_1 = K_2 = 0.1$.
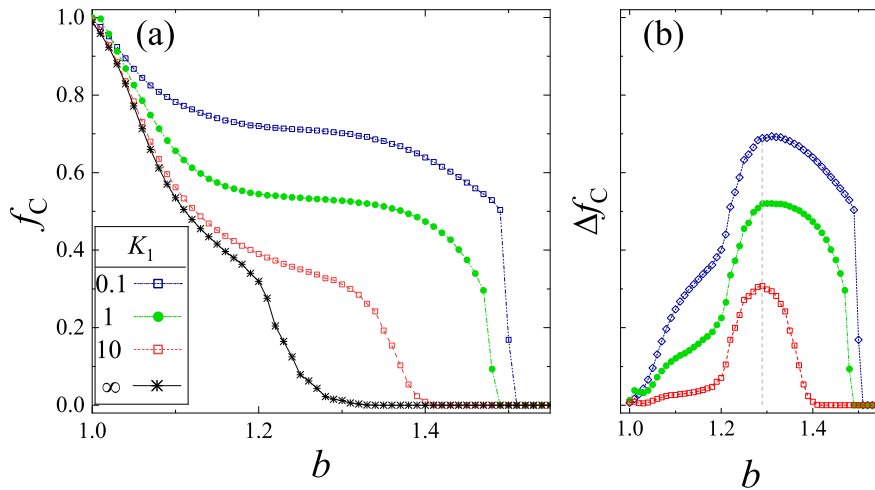

Fig. 3. (a) The fraction of cooperators f_C against the temptation parameter b at different K_1. (b) The difference in f_C, Δf_C, between that obtained at $K_1 = 0.1, 1, 10$ and $K_1 = \infty$. The dashed line marks the b value at which the maximum Δf_C can be obtained. Other parameters: $\tau_U = 100$, $\Delta\tau = 1$ and $K_2 = 0.1$.

range. It implies that, during the evolution, cooperators have better local environments, which favors the increase of persistence levels, and in contrast, for defectors, they tend to lower their persistence levels. Moreover, with the increase of τ_U, such effects become more distinct. The distributions of $\tilde{\tau}$ for cooperators are more concentrated close to τ_U and those for defectors are more close to τ_D.

As mentioned in the model, K_1 is a key parameter that determines to what extent τ_i is influenced by the environment comparison. The extreme value $K_1 = \infty$ fully overshadows the effects of the environments, in which case players alter their strategy persistence levels in a completely random way. When $0 < K_1 < \infty$, player i with $\Delta E_i(t) > 0$ is more likely to increase his strategy persistence level $\tau_i(t)$. Although he also has the possibility to decrease $\tau_i(t)$, the probability gets small as K_1 approaching to zero. In Fig. 3(a), we plot f_C against b at different K_1. One can observe that, in comparison with $K_1 = \infty$, f_C shifts upwards with K_1 decrease, indicating that the adaptive strategy persistence could improve cooperation better with small noise. In Fig. 3(b), we calculate the difference in f_C, denoted by Δf_C, between that obtained at $K_1 = 0.1, 1, 10$ and $K_1 = \infty$, respectively. We can see that, for these K_1, Δf_C first rises and then falls. In the range of b which favors the survival of cooperation at $K_1 = \infty$, f_C falls from 1 to 0 as b increases from 1 to 1.28, while the curves Δf_C with respect to $K_1 = 0.1, 1, 10$ are dramatically increased, which implies the promotion of cooperation is more efficient at intermediate b. For $b > 1.28$ where $f_C = 0$ for $K_1 = \infty$, Δf_C declines in consistence with the fall of f_C when b further increasing.

The positive influences of strategy persistence on the evolution of cooperation have been explained by the previous works [41–43]. In these works, all or part of the population are assumed to hold homogenous and fixed strategy persistence level. The cooperators could provide better support to their neighbors than defectors, which contributes to the formation
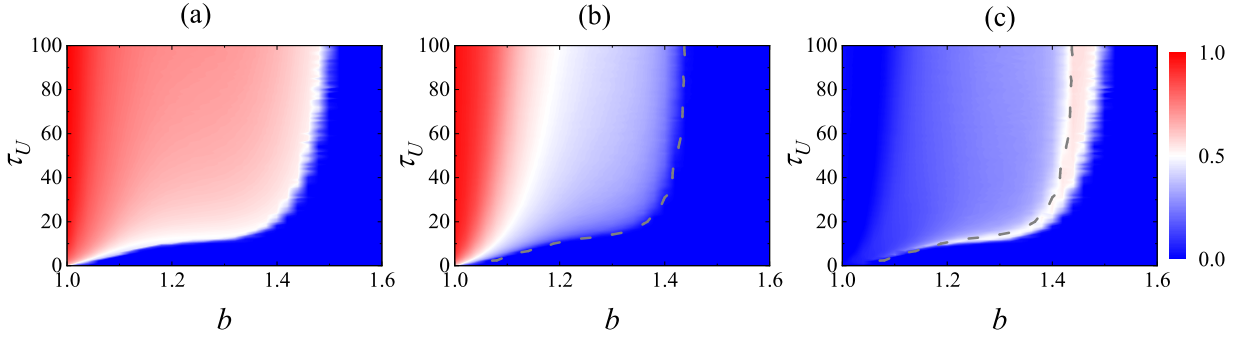
Fig. 4. Contour plots for the fraction of cooperators f_C in the plane of $b - \tau_U$ for two different cases: (a) Adaptive $\tau_i(t)$ base on the environment comparison. Other parameters: $K_1 = K_2 = 0.1$ and $\Delta\tau = 1$. (b) Fixed $\tau_i(t)$ which is equal to τ_U and uniform for all players. To do this, we set $\tau_i(0) = \tau_U$ and $\Delta\tau = 0$ for the whole population. Other parameters: $K_2 = 0.1$. The dashed line separates the two regions, the left is the coexisting region of cooperators and defectors and the right is the full-defector region. (c) The difference between the results obtained from the two cases. The dashed line is the same as that in panel (b).
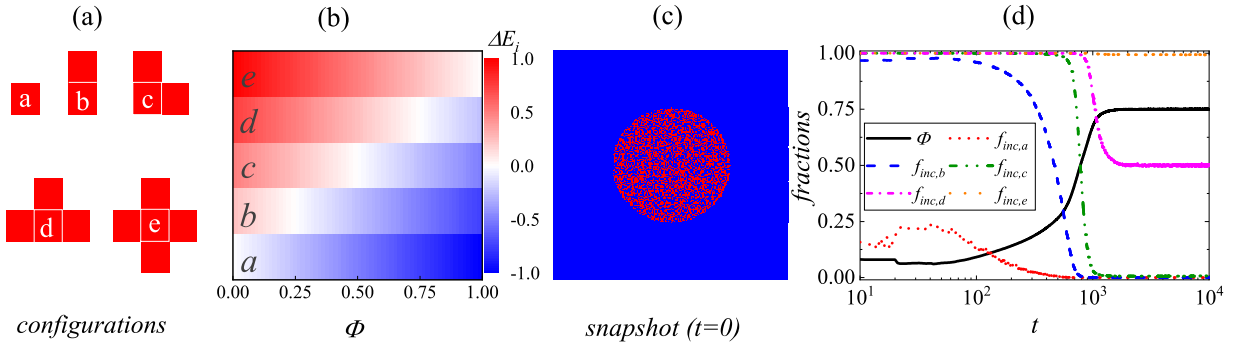

Fig. 5. (a) An illustration of the five possible configurations for a group centered by a cooperator on square lattice, denoted by a, b, c, d and e, respectively. For each group, only cooperators are presented. (b) The environment comparison ΔE_i in dependence on ϕ for the five possible cases of a cooperator i shown in panel (a). For each case, red represents $\Delta E_i > 0$ indicating an increase tendency of τ_i, while blue means $\Delta E_i < 0$ indicating a decrease tendency of τ_i. (c) A prepared initial condition, shown by the snapshot at $t = 0$, in which 20% players inside the circle are equally endowed with C (red) or D (blue) while the rest 80% are defectors. (d) Time series for the fractions of the cooperators in the five configurations $a - e$ whose $\tau_i(t)$ get increased at step t, denoted by $f_{inc,a}(t)$ (red), $f_{inc,b}(t)$ (blue), $f_{inc,c}(t)$ (green), $f_{inc,d}(t)$ (magenta) and $f_{inc,e}(t)$ (orange). The black solid represents the time evolution of the fraction of cooperators in the whole population, or the global cooperative environment $\phi(t)$. Other parameters: $L = 200$, $K_1 = 0.05$, $K_2 = 0.1$, $\tau_U = 20$, $\Delta\tau = 1$.

of cooperator clusters (C-clusters) and enhances network reciprocity. It has also be discovered that the cooperation level is positively correlated with the strategy persistence level. Then, we are necessary to examine how the model in this work differs from the previous studies, and whether it has some advantages over them. In Fig. 4 (a), we present the fraction of cooperators f_C in the plane of $b - \tau_U$ panel. For comparison, the results in the fixed persistence level case are presented by Fig. 4(b). As shown both in Fig. 3(a) and (b), f_C decreases with the increase of b as expected but increases greatly with the increase of τ_U, which is consistent with the discussions in Fig. 1 and Ref. [42]. For a better comparison, we calculate the difference between them and show the results in Fig. 4(c). We can find that, the adaptive persistence level introduced in this work always outperforms the fixed one case. Interestingly, such advantages expand first as b increases and reach the maximum around the dashed line, which marks the critical values of b that support the survival of cooperation in the case of fixed and homogeneous persistence level. Similar to Fig. 3, it implies that the environment-comparison-based strategy persistence performs better than the fixed one, especially at a certain moderate range of temptation parameter b.

In order to give a deeper insight into the microscopic mechanism, we present a brief analysis in Fig. 5. In strategy imitation dynamics, network reciprocity is known as cooperators clustering to make their own gains exceed the defector neighbours, and protecting themselves from being invaded. We would like to investigate how such reciprocity gets enhanced by the adaptive persistence level in this model. Assuming player i is a cooperator, we illustrate all the possible configurations he might confront as shown in Fig. 5(a). It can be easily calculated that $\varphi_a(t) = 0$, $\varphi_b(t) = 0.25$, $\varphi_c(t) = 0.5$, $\varphi_d(t) = 0.75$ and $\varphi_e(t) = 1$ for these five configurations, respectively. Then, for these configurations, we compute the dependence of ΔE_i on ϕ, as presented by Fig. 5(b). Obviously, $\tau_i(t)$ is likely to be increased for i in the configurations of b, c, d, e if $\phi < 0.25$, in configurations of b, c, d if $0.25 \leq \phi < 0.5$ and in configurations of c, d if $0.5 \leq \phi < 0.75$. Meanwhile, τ_a is hard to be supported by local environment while τ_e has a high probability to be favored. Then, we used a prepared initial condition with small $\phi(0)$, shown in Fig. 5(c), to investigate the evolution of the persistence levels for the cooperators with different configurations. We count the fraction of the cooperators who increase their strategy persistence levels at time step t in
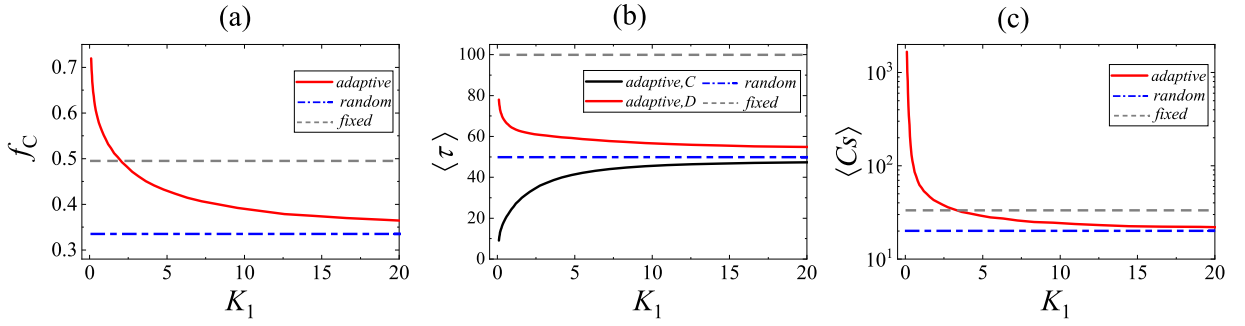
Fig. 6. The fraction of cooperators in the steady states f_C (a), mean strategy persistence level $\langle\tau\rangle$ (b) and the average size of cooperator clusters $\langle Cs\rangle$ (c) as a function of K_1. For each panel, three cases are considered: fixed τ_i (gray dashed line), adaptive τ_i (solid lines, red for C, black for D) based on environment comparison, and randomly changed τ_i (blue dot-dashed line). For the first case, τ_i is fixed to be 100 for the whole population throughout the evolution. For the latter two cases, $\tau_U = 100$, $\Delta\tau = 1$. Other parameters: $K_2 = 0.1$, $b = 1.2$. The results are obtained from averaging over 200 independent realizations.
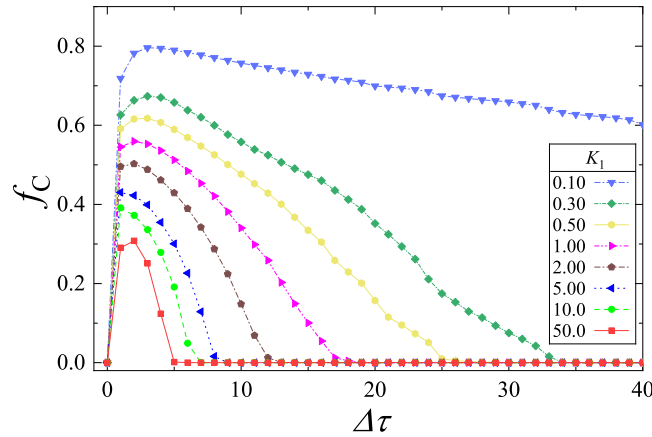

Fig. 7. The fraction of cooperators f_C as a function of $\Delta\tau$ for different noise intensity K_1. Other parameters: $b = 1.2$, $\tau_U = 100$ and $K_2 = 0.1$.

each configuration, denoted by $f_{inc,i}(t)$ and here i could be from a to e, and present the results in Fig. 5(d). Throughout the process, $f_{inc,a}(t)$ (red curve) keeps low implying that only a small fraction of cooperators with configuration a have their τ increase from the previous step. In the early stage when $\phi(t)$ is very low, $f_{inc,b}(t)$ (blue), $f_{inc,c}(t)$ (green) and $f_{inc,d}(t)$ (magenta) keep close to 1, indicating that the majority of cooperators who have at least one cooperator neighbors increase their τ at small $\phi(t)$. With the rise of $\phi(t)$, all $f_{inc,i}$ except for $f_{inc,d}$ and $f_{inc,e}$ drop to zero successively. The above analysis indicate that, for a cooperator i who has at least one cooperator neighbor, the adaptive persistence level based on the environment comparison has a strong effect to increase τ_i especially when ϕ is very low. Intuitively, for any cooperator, the increase of τ_i for cooperators can give more sustainable support to his cooperator neighbors and reduce the invasion chance of defectors. In addition, the clustering of cooperators not only enhances their mutual payoffs, but also improves the performance of local environments over the global one which in turn helps increase τ_i. Such effects become more prominent, particularly when the cooperation level is relatively low, because τ_i can be favored by more configurations. It explains why f_C is improved best at intermediate b [see Figs. 3(b) and 4(c)]. In contrast, due to mutual defection can only shorten the strategy persistence time of defectors, defector clusters are not supported and fragile during the evolution. As a consequence, the phenomena reported in Ref. [45], that zealot cooperators inhibit cooperation by continually contributing high payoffs for the exploitation of defectors, can never arise here.

Based on the above analysis, we further compare the impact of τ on cooperation promotion in three different situations where τ is fixed, randomly changed or adaptive based on environment comparison. Besides the fraction of cooperators, we also calculate the mean strategy persistence levels and the mean size of cooperator clusters. The results are shown in Fig. 6. As expected, for the adaptive case, small K_1 favors high τ for cooperators, but restrains τ for defectors [see Fig. 6(b)], which contributes to high cooperation level [see Fig. 6(a)] and large cooperator cluster size [see Fig. 6(c)]. Notably, Fig. 6(b) shows that, with the increase of K_1, $\langle\tau\rangle$ are rapidly converging to $\tau_U/2$, which suggests that the dynamics of τ becomes more random. As a result, the superiority of cooperators over defectors from strategy persistence decreases rapidly. Once K_1 exceeds a certain value, the adaptive case performs worse than the fixed $\tau = 100$ case where cooperators among C-clusters can provide longer and more stable supports for each other.
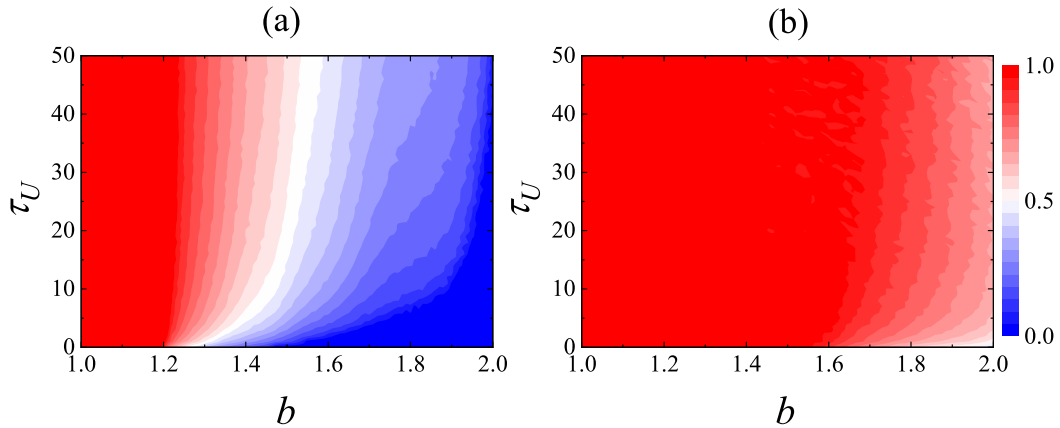
Fig. 8. (Color online) Contour plots for the fraction of cooperators f_C in the $b - \tau_U$ plane on Erdös-Rényi (ER) networks (a) and scale-free (SF) networks (b). The mean degree is 4 and the network size is 3000 for the two types of networks. Other parameters: $\Delta\tau = 1$, $K_1 = K_2 = 0.1$.

Fig. 7 reports the fraction of cooperators f_C against the increment $\Delta\tau$ at different noise intensity K_1. It is not surprising that small K_1 boosts high cooperation level regardless of $\Delta\tau$, which is consistent with the previous results. In case of $\Delta\tau = 0$, the model degrades to the traditional prisoner's dilemma game model, and cooperation can not emerge and persist at $b = 1.2$. Interestingly, f_C displays an optimal behavior against $\Delta\tau$. Once $\Delta\tau$ increases above zero, the cooperation level is immediately and dramatically enhanced. Then, the cooperation level f_C gradually decreases to zero with the further increase of $\Delta\tau$. The optimal f_C appears at very small values of $\Delta\tau$.

As explained before, higher τ_U provides a greater buffer for players to resist the environment fluctuation and thus to sustain the network reciprocity among cooperators even when $\Delta E(t)$ is transiently lower than zero. Actually, the role of $\Delta\tau$ is contrary to that of τ_U. Larger $\Delta\tau$ weakens such buffer, and therefore weakens the cooperators' reciprocity. We take an example for explanation. Considering two populations whose $\Delta\tau$ are set to be 20 and 50, respectively. For any player i in the first population and player j in the other, τ_i could be 0, 20, 40, 60, 80 or 100 while τ_j could be 0, 50 or 100. At the moment t, assuming both $\Delta E_i(t)$ and $\Delta E_j(t)$ are less than zero, then $\tau_i(t)$ is likely to be 80 for i with $\tau_i(t-1) = 100$ while $\tau_j(t) = 50$ if $\tau_j(t-1) = 100$. In consequence, players in the first population whose timers satisfying $80 \leq \ell_i \leq 100$ are ready to imitate strategies. Similarly, players in the second population with $50 \leq \ell_j \leq 100$ are ready to update strategies as well. Obviously, the interval [50,100] are much wider than [80,100], which leads a higher percentage of players to no longer persist and to update strategies in the next step. Therefore, large $\Delta\tau$ performs worse when facing bad local environments.

At last, we provide two contour plots for f_C in the plane of $b - \tau_U$ when simulating the model on Erdös-Rényi (ER) and BA scale-free (SF) networks, respectively. As presented in Fig. 8, we can find that the cooperation level is greatly improved as τ_U increases, which indicates that the cooperation promotion by the adaptive persistence based on environment comparison is robust to the structure of complex networks.

4. Conclusion

To summarize, we have studied an evolutionary prisoner's dilemma game model where players do not consider altering strategies at each step but preserve them for a period of time, which can be due to "inertia" in strategy switching [41] or avoiding the cost of decision making [38–40]. Particularly, here we assume that, the players can perceive both the local and global environments and adapt their persistence levels based on environment comparison. The results show that such an adaptive persistence may alleviate the situation of prisoner's dilemma and enhance network reciprocity among cooperators, especially under bad global environments for cooperation. The microscopic studies of evolutionary process suggest that small cooperator density in the population supports a greater variety of cooperator configurations. Moreover, by comparing the results with the fixed and randomly changed cases , we emphasize that the environment comparison plays a key role in improving cooperators' persistence levels but impedes that for defectors, which contributes to further boost of cooperation. Furthermore, we show that increasing the upper limit of the persistence level τ_U or decreasing the increment $\Delta\tau$ may enlarge the buffer of τ to resist the short-term fluctuations of environment changes, which helps stabilize the mutual favor between cooperators .

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