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Optimization of mobile individuals promotes cooperation in social dilemmas

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ABSTRACT

We study how mobile individuals affect the evolution of cooperation in social dilemmas. In doing so, we consider two types of players. The traditional type simply copies the most successful strategy in its neighborhood in order to improve its future payoff, while the advantageous type moves away in the hope of settling in a better community. We show that the introduction of the advantageous type leads to larger and more compact cooperative clusters in the prisoner's dilemma game. This in turn facilitates the evolutionary stability of cooperation even under adverse conditions that are characterized by high temptations to defect. We also verify that the average payoff of a community unit remains proportional to the number of cooperators in this community, which hence indicates that the players pursuing mobility to attain a competitive advantage also foster cooperation in their new communities. Another way to communicate this result in the light of the costs associated with moving is to say that optimal mobility, such that yields higher payoffs to the individual who moved and the community as a whole, is similar to the optimization of the allocation of limited resources. We thus hope that these results will shed new light on how to effectively allocate resources and how to optimize mobility for optimal cooperation.

1. Introduction

According to Darwin's theory of natural selection, the evolution generally favors selfish individuals who give their own wellbeing top priorities. Nevertheless, the success of humans has been to a large degree attributed to our quite special ability to cooperate in large groups and among unrelated individuals [1,2]. In addition, such cooperation is usually involved in a group of individuals and could not be reduced to the sum of related pairwise interactions [3–5]. The sustainable development of modern human societies is up to widespread cooperation among individuals, groups, and nations. Deep and extensive cooperation is particularly crucial when facing common challenges like epidemics [6], shortages of natural resources, or social unrest. In contrast, individual solutions often lead to inefficient resource allocations and failure of coordination [7]. Therefore, how to improve cooperation among selfish individuals remains an evergreen challenge of perpetual significance for the wellbeing of human societies.

Attesting to this fact, cooperation in human societies has attracted much attention in recent decades [2,8–10]. Theoretical models suggest that social networks may affect the evolution of cooperation. An effective mechanism to enhance cooperation is to enlarge the cooperative clusters by punishing defectors or rewarding cooperators [2], as well as heterogenous structures of social networks [11–15]. The experiments have verified that voluntary costly punishment could help maintain cooperation which persists for multiple rounds and spreads up to three degrees of separation [16]. It is generally also believed that dynamic networks would foster cooperation [17–20]. Nevertheless, individuals may be reluctant to switch partners when the costs associated with building new links are high. Further, adaptive approaches with endogenous self-organization where the network presents the plasticity or responds to specific feedbacks could outperform global strategies [21–28] and even the most capable individuals if they remain in isolation [29]. Nevertheless, research has also shown that static networks could still lead to a stable and high level of cooperation when the benefits from the cooperation are greater than the

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number of neighbors in the network [30]. Cooperation through the mechanisms of kin selection, direct reciprocity, indirect reciprocity, network reciprocity and group selection have also been found to favor cooperators and suppress free-riders, and are thus likely to feature more prominently in future rounds [31].

In the evolution of networks adaptive migration requires only local information in game interactions, responds accordingly to the change of local environment and promote cooperation in spatial games [8,32,33]. Thus it has the potential to inspire unique yet mobile individuals to locate at the right spot to achieve their own goals as well as group prosperity. For example,a risk-driven migration activated according to the difference between the actual contributions and the declared target promotes the cooperation much more effectively than under the action of manually determined migration rates [34]. And, if individuals select their most successful neighbor and invest towards the related local community, the cooperation would prevail even in harsh environment [35]. Parent-preferred dispersal [36] and mobility via emergent self-assortment dynamics [37] also promote the evolution of the cooperation. Besides, mobility based on cost could regulate effectively the rate of movement [33]. However, its effect has not been understood clearly. Specifically, when the temptation is not too high, e.g., $b \leq 1.3$, individuals move away to avoid defectors on the adaptive mechanism [8]. However, when temptation exceeds the threshold, this punishment for defectors will not regulate behaviors.

For a firm pursuing the apparent conflicting objectives of profit excellence and cost-effectiveness at the same time, a key approach is managing and organizing its valuable human resources to achieve sustainable competitive advantage to outperform other firms in its peer group. For a society, the sustainable development of a group is depending on the right utilization of resources, which means not only natural resources, such as oil, water and etc, but also refers to the human resources, material and financial resources in social and economic activities. Adaptive cooperative clustering and assortative mixing in dynamic networks has proven a crucial mechanism to promote cooperation with limited resources [38,39]. Thus it may provide an effective way to allocate these resources precisely and outperform their rivals with reduced cost for both firms and societies.

In this paper we aim to optimize the cooperation among selfish individuals with the presence of the migration cost. More specifically, we try to promote the cooperation by improving migration efficiency of cooperative clusters even under the circumstance of higher temptation $b \geq 1.4$. To this end we construct a prisoner's dilemma game with temptation. In the game there are dynamic interactions of both cooperators and defectors. Each individual has two approaches to improve his/her payoffs, either copying the strategy earning highest payoff in his/her neighborhood [10] or moving away to rebuild new interactive relationships. We consider the following scenario where a normal individual in the game tries to avoid the interaction with a defector, since there is no payoff for his/her own. As a result, such individuals may devise various approaches by breaking links with them, moving away to seek new friendly neighbors, and etc. In addition, we assume there are also advantageous individuals who cherish community prosperity either for better condition to live, or for gaining respects from community inhabitants. If they have the ability to spot an empty site where they could bring higher community interest for both himself and potential community, they may seize the chance to move away.

Our results demonstrates that advantageous individuals help extricate the situation from dilemmas in case of higher temptation. And as long as the cooperation is activated from a low mobility, its level would keep high and not proportional to the rate of mobility. We further presents that large cooperative clusters with the presence of advantageous individuals are stable enough when confronting challenges from defectors. Such mechanism is strong over time and could get more and larger cooperative clusters, and the system ends up with a stable state of high cooperation level. We show mathematically that the average payoff of the community is proportional to the number of cooperators, which signifies that the mobility itself cherishes actually cooperative behavior.

2. Model

Here, we considered a $M \times M$ regular and periodic lattice with $< k >$=4, where sites and edges represent individuals and their interactive relationships respectively. Initially, individuals are distributed throughout the whole lattice with 30% empty sites randomly [8,43]. Individuals has two strategies to choose in the process of decision-making, either cooperate (C) or defect (D). In each round x, individual i plays games with his/her opponents one by one to gain payoff P_i, which is a summarization of payoff earned from each interaction with her direct neighbors. The payoff for i playing with one of her direct neighbors j depends on both her own strategy and j's strategy, which is calculated by the model of prisoner's dilemma games (PDG). Both cooperators receive rewarding payoff R. Both defectors get punishment payoff P. A defector gains temptation payoff T for unilateral defect behavior, and the cooperator gets sucker's payoff S accordingly. Note that, both inequalities $T > R > P > S$ and $2R > P + S$ are satisfied for PDG. For simplicity, we set R=1, S=0, $T = b$ ($1 < b < 2$, temptation factor), and $P = 0$ for a weak PDG. Further, we adopted another two parameters $D_g = T - R$ and $D_r = P - S$ to depict dilemmas with different strength. Both inequalities $D_g > 0$ and $D_r > 0$ are satisfied for PDG. Particularly, large D_g signifies the high payoff gap for a defector, whereas big D_r means sever loss for a sucker.

In this model, there are two types of individuals, normal ones and advantageous ones. The density of latter is designated as ρ_A, accordingly, the density of former is 1-ρ_A. The status is once initialized at the beginning, it is changeless all the time. Each individual has two approaches to improve his/her payoffs, either copying the strategy earning highest payoff in his/her neighborhood [10] or moving away to rebuild new interactive relationships. According to his/her status, the aim for mobility is different too. To be more specific, a normal individual moves away to avoid defectors in his/her community and looks forward to meeting new potential cooperators. The probability is calculated by the equation $\delta = N_d/(N_d + N_c)$. Parameters N_d and N_c are the number of defectors and the number of cooperators in their community respectively. Theoretically, with more defectors comes more probability to move away. Whereas the latter would move into an empty site where he/she could bring higher interests to the new community (including him/her-self). Considering mobility cost in real life, each individual is assumed to choose only one of both approaches, either update strategy or move. Furthermore, a parameter α is introduced here to depict success rate of mobility for the sake of possible failure of mobility. Thus, the probability that a normal individual moves is $\delta \times \alpha$, and the probability of updating strategy is 1-δ. For an advantageous individual, when he/she could bring more payoff to the potential community, he/she will move with probability α. Otherwise, he/she will update strategy.

The evolutionary process is simulated by the Monte Carlo method. Firstly, an individuals i will be chosen randomly. Then, i plays games with her opponents one by one to earn payoff. Next, i will either copy the strategy obtaining highest payoff in her community, or move away. Theoretically, each individual has an opportunity to improve her payoff in a time step (marked as t). In this paper, we aim at seeking out how to enhance cooperation level of the system. Therefore, we focus on the frequency of cooperation f_C, which could characterize the cooperation level of the system. We calculate f_C by the equation $f_C = N_{CW}/(N_{CW} + N_{DW})$,

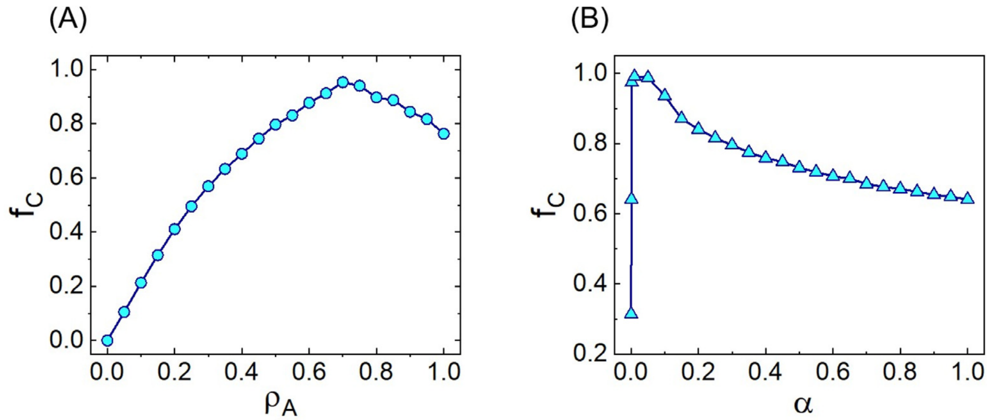

Fig. 1. (color online) Cooperation frequency (f_c) as a function of the density of advantageous individuals ρ_A (A), and as a function of of α (B). The parameters set: b=1.5, α=0.1 in panel (A), and ρ_A=0.7 for panel (B).

where, both parameters N_{CW} and N_{DW} are the number of cooperators and the number of defectors in the whole grid respectively. In addition, each data point is obtained by averaging out last 20000 time points (from t=480000 to t=500000) in each realization after system turns into a dynamic equilibrium. In order to counteract the impact of initialization, we average another 20 different realizations. The parameter is set as follows throughout this study, M=128,R=1 S=0, and P=0.

3. Simulation results

We start with the representative results showing how the cooperation frequency (f_C) evolves with the population density of advantageous individuals (ρ_A), as shown in Fig. 1 (A). In case of ρ_A=0.00, the individuals are all normal ones, who promote payoff according to their own situation, either update strategies, or move away to avoid defectors. It is observed that each individual tends to defect for high temptation, such as b=1.5. Here, adaptive mobility [8] loses impacts on promoting cooperation for there are always defectors around wherever they head, which forces the individuals into life on the run. This situation is even worse than the case that all individuals stay put and survive in clusters at least (f_C=0.31). However, the situation is totally different if there are some individuals who move for producing more benefits to new communities than that in current communities. As ρ_A increases, more and more advantageous individuals are involved in mobility to produce higher average payoff of communities, which extricate possibly the situation from dilemmas. Particularly, the cooperation level peaks about 0.95 when $\rho_A = 0.7$. As ρ_A continues to increase, the f_C declines slowly. Note that the value of f_C is about 0.76 when ρ_A=1.00. Even so, the cooperation level is still far higher than that of all normal individuals present.

With uncertainty and objective factors in real life, not all mobility could be achieved successfully. We now show how f_C changes versus success rate of mobility (α) in panel (B). For α=0.00, all individuals stay put. In this condition, cooperators survive in clusters to gain reward payoff. It is observed that f_C is about 0.31. Remarkably, the value of f_C sharply increases and peaks when limited individuals move successfully. However, as α increases, f_C drops away slowly. As to the results that cooperation level is not directly proportional to the success rate of mobility, we have two considerations. The first reason is big expense for mobility. Bigger α signifies that more individuals would move successfully and giving up the opportunity of updating strategies. The another reason might be the high mobility impairing the effects of network reciprocity. Even so, mobility is still far more effective on promoting cooperation than staying put in the case of ρ_A=0.70 at any value of α.

Considering the potency of the mechanism, we try to seek out what dilemmas where this mechanism are effective on promoting cooperation. As well as to figure out what difference on enhancing cooperation between with and without advantageous individuals present. Two parameters D_g and D_r are used to characterize the strength of dilemmas, characterizing high payoff gap for defector's and sever loss for sucker's respectively. Here, $D_g = T - R = b - 1$ and $D_r = P - S = S$. Any of D_g or D_r rises, the strength of dilemma increases, and cooperation is hard to spread. As is shown in Fig. 2, the effective scope on cooperation presents ladder-shape in both panels. However, the area of trapezoid for ρ_A=0.7 in panel (A) is larger than that of ρ_A=0.0 in panel (B). Impressively, in case of same D_r, D_g in effective scope in panel (A) is higher than that in panel (B). The similar trend is also observed for D_r in terms of same D_g. Comparing with the adaptive mechanism, the present mechanism with advantageous individuals present shows remarkable universality on enhancing cooperation.

Since our mechanism has remarkable potency and universality as described above. It is interesting to investigate how advantageous individuals contribute to promoting cooperation in detail. In view of the fact that the interactive relationships among individuals are structured, we explore it from dynamic spatial snapshots for two representative cases with and without advantageous individuals. Generally, the number of cooperators determines the level of cooperation. And the size of cooperative clusters affects the stability of cooperation. Therefore, we also calculate the size and the number of cooperative clusters at different time for representative ρ_A=0.70. Due to the stability of cooperative clusters of different size, we plan to sort these clusters according to size. The average size of cooperative clusters is calculated about 9.10, marked as $\lambda_{AVG} = 0.91$. Therefore, we separate the cooperative clusters into two types, small cooperative clusters ($\lambda \leq 9$) and large cooperative clusters ($\lambda \geq 10$). The proportion of cooperative clusters of both small and large cooperative clusters in cooperative population, as well as the proportion of defectors in whole population are calculated at different time respectively, which are shown in Fig. 3 (I) to (L) accordingly.

For the sake of comparison, the initial state of both representative cases are the same, as shown in panels (A) and (E). For ρ_A=0.00, a few tiny cooperative clusters appear when $t = 10$ (B). Gradually, some of cooperative clusters die out, and some of them grow large when $t = 100$ (CC. However, these small clusters are so vulnerable that most of cooperators can not survive in face of constant challenges from defectors eventually (D). The value of f_C in panels (A) to (D) is 0.50, 0.22, 0.06 and 0.00 respectively. In case of ρ_A=0.70, most of cooperators survive in small cooperative

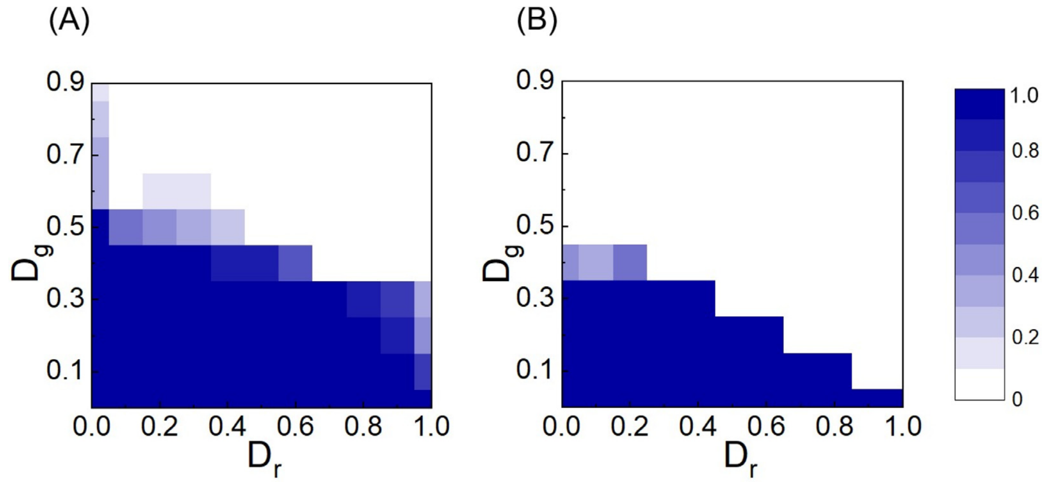

Fig. 2. (color online) Color-codes of f_c in D_g and D_r space for $\rho_A = 0.70$ (A), and $\rho_A = 0.00$ (B). Here, $D_g = T - R$ and $D_r = P - S$, and other parameters is α=0.1.

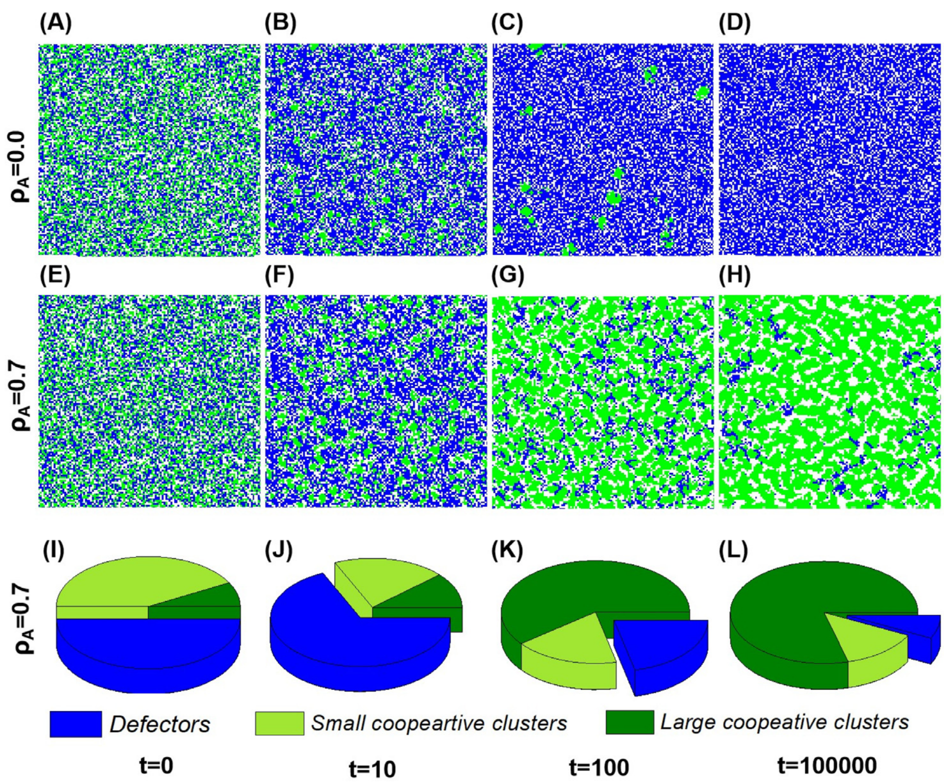

Fig. 3. (color online) Evolution of spatial patterns for representative ρ_A. The top panels(A)-(D) are for ρ_A=0.00, and corresponding value of f_C is 0.50, 0.22, 0.06 and 0.00 respectively. The middle panels (E)-(H) are for ρ_A=0.70, and the corresponding f_C is 0.50, 0.32, 0.79 and 0.93 respectively. Color coding is as follows: green represents cooperator, blue is defector, and white is empty. For the sake of comparison, 50% of individuals are cooperators and 50% of individuals are defectors, who are distributed on the whole lattice with 30% empty sites initially. The bottom panels of pie chart (I)-(L) is the proportion of both small and large cooperative clusters in total cooperative clusters, together with the proportion of defectors in the whole population for case of ρ_A=0.70 at different time respectively. Other parameters are b=1.5, α=0.1.

clusters (I). After fierce competitions between cooperators and defectors, the number of defectors increase sharply, whereas most of small clusters disappear(F). And only large cooperative clusters hold with a slight upturn when $t = 10$ (J). Interestingly, it is observed that a large number of cooperator organized in large clusters survive when $t = 100$ (G). With decrease of defectors, the defeat of defectors spares the prosperity of cooperators (K). As time goes by, this trend continues. The cooperative clusters evolve to be more compact and larger ones (H), which are stable enough when confronting challenges from defectors, and the ratio of defectors shrinks further (L). The system terminates into a dynamic yet stable state of high cooperation level. The value of f_C in panels (E) to (H) is 0.50, 0.32, 0.79 and 0.93 respectively.

To verify the robustness of this mechanism, we initialize a state which favor defectors. With defectors surrounded, a small bunch of cooperators are located in the center of the lattice. As is shown in Fig. 4, the evolutionary process is investigated from two aspects. Firstly, we explore how row sites at 64th column on lattice evolve over time (splicing representative fragment of evolutionary process) (A). Secondly, the whole snapshots at representative time points will be investigated respectively (B)-(E). Remarkably, it is shown that these few tiny cooperative clusters get more

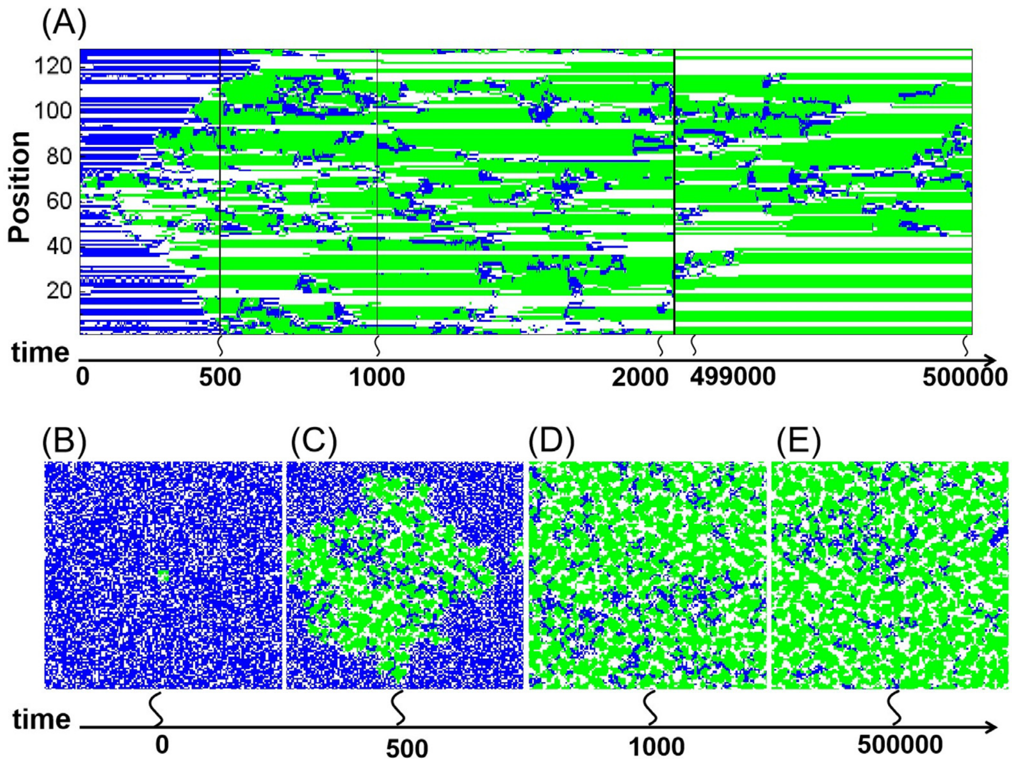

Fig. 4. (color online) The representative evolutionary patterns with a bunch of cooperators besieged by all defectors. Evolutionary process of all row sites at column $M = 64$ over time (A) and the evolutionary patterns at according time points, $t = 0$ (B), $t = 500$ (C), $t = 1000$ (D) and $t = 500000$ (E). The according value of f_C is about 0.002 ($f_C = \frac{6*6}{128*128}$), 0.359, 0.818 and 0.884 respectively. Other parameters are b=1.5, α=0.1.

and larger, provided there is enough time to evolve. Just as a single spark starts a prairie fire, the system ends up with a dynamic equilibrium state, where cooperators dominate eventually.

Theoretically, cooperators do not have advantages to earn higher payoff than defectors under the condition of high temptation for a pair of parters. In spatial dilemmas, one way out for cooperators is pulling together to receive reward payoff to survive, compact cooperative clusters in particular. For example, we assume a compact unit community, where there are 5 cooperators and a loose cluster, where there are 4 cooperators only and 1 empty site. In the compact cluster, the average payoff is $\prod_{AVG} = \frac{4\times R+4\times R}{5}$. Since R=1, $\prod_{AVG}$ is written as $\prod_{AVG} = \frac{4\times 1+4\times 1}{5} = \frac{8}{5}$. In the loose cluster, the average payoff is $\prod_{AVG} = \frac{3\times R+3\times R}{4}$. With R=1, $\prod_{AVG}$ is written as $\prod_{AVG} = \frac{3\times 1+3\times 1}{4} = \frac{6}{4}$. Obviously, the average payoff of a compact cluster is higher than that of loose cluster. In addition, the compact cooperative clusters are stable when blocking invasion from defectors [43].

We try to lay out an analytical perspective on this mechanism. We still consider a unit community, where there are 5 regular lattice sites. For simplicity, the individuals are distributed randomly on the sites with 20% empty sites. The individual i is assumed to locate at the center site. Thus, the population density of this community is about 80.00%. Within this community, the number of cooperators is designated as χ_C ($\chi_C \in [0, 4]$), and the number of defectors is χ_D ($\chi_D \in [0, 4]$). Thus, the total number of individuals in the community is $\chi = \chi_C + \chi_D$ ($\chi = 4$ in this unit community) accordingly. Moreover, we assume the probability that i cooperates is σ, accordingly the probability that i defects is 1-σ. Thus, the average payoff of the community $\prod_{AVG}$ can be written as

$$\prod_{AVG} = \sigma \times \prod_{C} + (1-\sigma) \times \prod_{D} \tag{1}$$

where, $\prod_C$ is the average payoff in unit community when i cooperates, calculated as

$$\prod_{C} = \frac{\chi_D \times S + (\chi_C - 1) \times R + (\chi_C - 1) \times R + \chi_D \times T}{\chi} \tag{2}$$

And, $\prod_D$ is the average payoff in unit community when i defects, calculated as

$$\prod_{D} = \frac{\chi_C \times T + \chi_C \times S + (\chi_D - 1) \times P + (\chi_D - 1) \times P}{\chi} \tag{3}$$

Since we set parameters: $S = P = 0$, $R = 1$, $T = b$, the average payoff of the community $\prod_{AVG}$ can be written as

$$\begin{aligned}\prod_{AVG} &= \sigma \times \frac{2(\chi_C-1)+b\chi_D}{\chi} + (1-\sigma) \times \frac{b\chi_C}{\chi} \\ &= \frac{\sigma(2\chi_C-2+b\chi_D-b\chi_C)+b\chi_C}{\chi}\end{aligned} \tag{4}$$

Since $\chi_D = \chi - \chi_C$, $\prod_{AVG}$ can be written as

$$\begin{aligned}\prod_{AVG} &= \frac{\sigma(2\chi_C-2+b(\chi-\chi_C)-b\chi_C)+b\chi_C}{\chi} \\ &= \frac{\sigma(2\chi_C-2+b\chi-2b\chi_C)+b\chi_C}{\chi}\end{aligned} \tag{5}$$

Actually, $\sigma = \frac{\chi_C}{\chi}$, thus, $\prod_{AVG}$ can be written as

$$\begin{aligned}\prod_{AVG} &= \frac{\frac{\chi_C}{\chi}(2\chi_C-2+b\chi-2b\chi_C)+b\chi_C}{\chi} \\ &= \frac{2(1-b)\chi_C^2+2(b\chi-1)\chi_C}{\chi^2}\end{aligned} \tag{6}$$

where, χ is the total number of individuals, which depends on the population density. Here, population density is a constant, $\chi = 4$. $\prod_{AVG}$ can be written as

$$\prod_{AVG} = \frac{(1-b)\chi_C^2+(4b-1)\chi_C}{8} \tag{7}$$

Thus, the average payoff of the unit community $\prod_{AVG}$ could be regarded as the function of the variable χ_C in a certain dilemma.

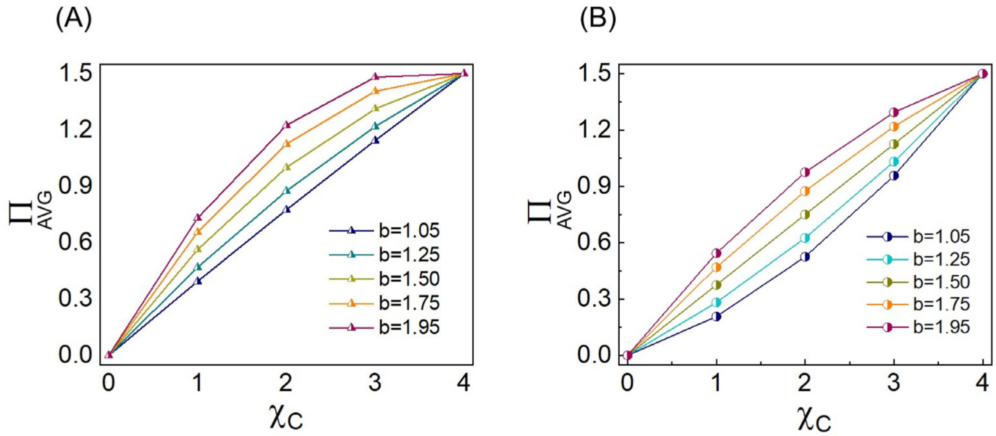

Fig. 5. (color online) the average payoff of the unit community $\prod_{AVG}$ as a function of the number of cooperators χ_C in weak PDG (A), and in pure PDG (B). The parameters are $T = b$, $R = 1$, $P = 0$, S=0.0 in panel (A) and S=-0.5 in panel (B).

In order to get a direct image of how $\prod_{AVG}$ change over χ_C ($\chi_C \in [0, 4]$), we calculated the curves for different b, as shown in Fig. 5. In panel (A), it is shown that $\prod_{AVG}$ is positively correlated with χ_C. Besides, it is observed that $\prod_{AVG}$ for bigger b is higher than smaller b. In weak PDG, we only consider the temptation payoff for a defector and ignore the sucker's payoff for the cooperator, for the sake of simplifying complex issues to see the essence beneath phenomena. In order to clarify this, we further consider a pure PDG, where $T = b, R = 1, P = 0, S = -0.5$. As shown in panel (B), the case $D_g = D_r$, such as $b = 1.5$, $S = -0.5$, $\prod_{AVG}$ is linear proportional to χ_C (marked as baseline). For $D_g > D_r$, $\prod_{AVG}$ is higher than baseline curve. For $D_g < D_r$, $\prod_{AVG}$ is lower than baseline curve. Nevertheless, $\prod_{AVG}$ is positively correlated with χ_C, which signifies that the mobility itself actually cherishes cooperative behavior, although advantageous individuals may move in pursuit of higher community payoff.

Despite of the fact that an advantageous individual is one of community members, he/she will share community payoff with others. However, what can not be ignored is that the payoff he/she gains in the new community may be lower than he/she gained in the previous site. In real life, most individuals barely move for producing higher payoff for other unless their own payoff is higher, or not lower at least. Considering this actual situation, we run another simulation, where advantageous individuals will move if the following two conditions are satisfied. Besides the first condition that they could produce higher benefits to new community where they will settle, the second condition is that their own benefits will not be cut down after mobility either. We compare this new mechanism with the present mechanism meeting only first condition. As is shown in Fig. 6, both f_C curves present the same shape. However, the f_C of the mechanism meeting both conditions is higher than the focal mechanism. Particularly the positive gap between two curves broadens as ρ_A increases. The comparison results reflects the fact that individuals may move for increasing their own payoff, actually their mobilities are effective to promote cooperation as long as the mobilities could bring higher benefits to new communities.

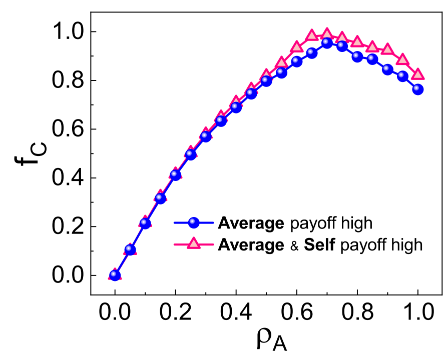

Fig. 6. (color online) The comparison of both mechanisms which satisfy both conditions or first condition. Here, the first condition is that their mobility can bring higher benefits to new community. the second condition is that their own benefits will not be cut down. Other parameters are b=1.5, α=0.1.

4. Discussion

The previous study on the adaptive mechanism where individuals move away to avoid defectors [8,43] showed the mechanism could enhance cooperation effectively when temptation is not too high, such as $b \leq 1.3$. Actually, it is more like a punishment for defectors that individuals would rather move away than interacting with them. However, the punishment seems not severe enough to regulate behaviors when temptation exceeds a threshold. In case of larger b, such as $b \geq 1.4$, this mechanism loses impact on enhancing cooperation. And the system ends up with a state of no cooperation. We attribute the failure to the big expense for mobility where more individuals give up updating their strategies, and the high mobility impairs the effects of network reciprocity [43].

In such a dilemma, it is impressive to find that the situation could be reversed if there are individuals who move to produce higher payoff to new communities where they will settle down. Even some individuals who may care only about their own payoff, their mobilities could promote cooperation effectively among whole population if only they could bring higher payoff to their new communities without compromising the original intention of their mobility. We investigated the dynamic spatial patterns of ρ_A=0.70 in high temptation. We have observed that large cooperative clusters play a key role in wining back lost territories and fighting to take over defecting neighborhoods. Besides, the cooperative clusters are compact ones, where cooperators gain higher payoff than that in loose or small clusters. Technically, we further created a more favorable situation for defectors, where only a small crowd of cooperators (6×6 cooperators in 128×128 lattice, f_C is about 0.002, neglecting empty sites) centered with all defectors surrounded initially. Despite of the condition against cooperators, the population of cooperators still could continue to increase, and the system terminates into a dynamic yet stable state that is characterized with a high cooperation level, which reflects that our results are robust.

The key issue is to determine how larger and more compact cooperative clusters could evolve? As to the reason why relatively tiny cooperatives clusters could take almost over the whole lattice, we refer to preceding research [40–42]. By analyzing this mechanism, it is verified that the average payoff of the community is proportional to the number of cooperators. Although individuals may move in pursuit of higher payoffs for their community and themselves, actually the mobility itself cherishes cooperative behavior. Furthermore, the behavior that encourages individuals to move and produce higher community payoffs to both the new community and themselves is kind of optimizing the allocation of human resources. This behavior could thus bring prosperity to the community, as well as to the society as a whole, which is composed of numerous unit communities. We also note that the level of cooperation could be remarkable when the mobility is limited, where direct reciprocity still works well [43]. However, if mobility is too expensive, it may wish away most of the chances for prosperity. We hope that our results may shed new light on how to effectively allocate limited resources. In the future, mechanisms as studied in this paper could also be studied in conjunction with positive and negative cooperation incentives, as very recently studied for example in [44].

Declaration of Competing Interest

Matjaz Perc is Editor of Chaos, Solitons & Fractals. In keeping with Elsevier's guidelines on potential editorial conflicts of interest, manuscripts coauthored by one of the Editors will be handled fully by other Editors or the Editor-in-Chief in an undisclosed review process. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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