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A limited mobility of minorities facilitates cooperation in social dilemmas

Wen-Jing Li[a], Luo-Luo Jiang[b,*], Matjaž Perc[c,d,e]

[a] College of Information Engineering and Art Design, Zhejiang University of Water Resources and Electric Power, Hangzhou, Zhejiang 310018, China
[b] School of Information Management and Artificial, Zhejiang University of Finance and Economics, Hangzhou, Zhejiang 310018, China
[c] Faculty of Natural Sciences and Mathematics, University of Maribor, Koroška cesta 160, 2000 Maribor, Slovenia
[d] Complexity Science Hub Vienna, Josefstädterstraße 39, 1080 Vienna, Austria
[e] Department of Medical Research, China Medical University Hospital, China Medical University, Taichung, Taiwan

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ABSTRACT

Individuals often move to distance themselves from defectors, or to seek better chances for higher payoffs, for example moving from rural to urban areas. Regardless of the reason, however, moving frequently also means alienation, which in turn means bearing costs for seeking new opportunities. With this motivation, we study a prisoner's dilemma game, where individuals with defectors in their communities either move or update their strategy. We find that the alienation from defectors reinforces larger and more compact cooperative clusters. However, the number of cooperative clusters depends on the viscosity of the interaction network, where network reciprocity still works well. And it is the fine-tuned interplay between the mobility to alienate from defectors and a still functioning network reciprocity that works best in promoting cooperation. Our results suggest that a limited mobility of minorities could spare public resources in social dilemma situations more effectively than reward and punishment.

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1. Introduction

The remarkable progresses of human beings come down to amazing capability of extensive cooperation from every aspect [1–3]. However, we should do better than we used to do for the sake of potential challenges, such as infectious diseases, limited resources, etc. It is intriguing to figure out what fosters cooperative behavior and how the social environments evolve together with cooperative behavior [4,5], because human cooperation can not be simply explained by existing theories.

There are five rules that nature selection favor cooperation, kin selection, direct and indirect reciprocity [6,7], group selection [8,9], network reciprocity [10–12]. Besides, individuals in real life may cooperate for various reasons, such as rewarding extra incentive [13], avoiding punishment [14], moving for success [15] or avoiding defectors [16,17], potential influence [18,19], etc. Aiming at finding out much more on cooperation, scientists have been conducting extensive researches either theoretically or experimentally mainly on the interactions among individuals, such as co-evolution of both game dynamics and network structure, where players either build interactions dynamically [20,21] or move away to alter their interacting neighbors. Particularly, as a fundamental trait in humans and animals, mobility could reduce competitions among

* Corresponding author.
E-mail address: jiangluoluo@gmail.com (L.-L. Jiang).

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individuals for local limited resources and prevent retaliating against each other tit-for-tat, which thus attracts lots of attention in the process of exploring effective mechanisms.

Referring to studies on mobility, there are theoretical or experimental researches on mobility, which are mainly focusing on mobility driven by some factors [15,16,22–24], such as higher payoff, etc. These mechanisms of mobility are involved in seeking cooperative partners or avoiding defecting neighbors. Helbing and Yu found the mobility into a cooperative environment could cause the outbreaking of cooperation [15], as long as obtaining the information predicting all potential partner's future behavior, as well as a premise that current cooperators would be still good partners in the next round. In reality, it is not easy to acquire detail information in community. A further research on mobility with only limited local information shows that the adaptive mobility promotes cooperation effectively [16]. To study whether cooperation comes from the mobility experimentally, Efferson et. al. conducted two sets of behavioral experiments where players in one group stay put, whereas players in other group are allowed to move in a lattice with knowing the number of defecting neighbors. Their results show that mobility with limited information promotes cooperation without considering the expense of mobility [23].

Despite of vast studies on mobility, far more work to reveal its essence is calling. There needs a universal yet simple model, which could provide a straight and distinct insight into this mechanism. Particularly, the expense for mobility should be considered in the model. Actually, the first response for most individuals suffering defectors is alienation from them. For an individual, the defectors are actually exploiters, who gain higher payoff by impairing the opponent's benefit instead of helping each other to receive rewarding payoff. The individual in the cooperative clusters, whether a cooperator or a defector, gains higher payoff than that earned at defector neighborhood or at boundary between cooperative cluster and defectors. Thus, an individual would like to interact with cooperators. For a group, defectors undermine the whole benefits of group. In addition, they may be a negative model for others to imitate due to higher payoff earned through exploitation, which may induce unpredictable dilemmas.

The common behavior that alienating from defectors without interacting with them is more like a punishment theoretically. No interactions, no gains. However, it might favor defectors to spread into cooperative clusters by the fact that a defector may alienate from other defectors. Therefore, we try to construct a simple yet universal model, where the individuals either move with a probability if there is a defector in their communities, or update strategies by social learning. One can not sell a cow and drink the milk, thus the individual will give up the opportunity to update strategy if he/she moves successfully, which is the opportunity cost for mobility. Firstly, we investigated the impact of mobility on cooperative clusters formation. Next, we explored cooperation level in the dynamic interaction network with different viscosity, which is related with probability of mobility. At last, we tried to seek out the mechanism of the mobility with limited information.

2. Model

Here, social interaction among players is simulated by a $M*M$ regular lattice with node degree $<k>=4$ (Von Neumann neighbors), where each node is occupied by a player or empty randomly, and the player interacts with the neighbors linked with himself/herself. Each player can either cooperate or defect. Accordingly, he/she gains different payoff, which depends on both himself/herself and his/her opponent. Here, we consider a Prisoners' Dilemma Games (PDG), where the reward for mutual cooperation is R, the punishment for mutual defection is P, the sucker payoff is S, and the temptation to defect is T. For PDG, these four parameters are required to satisfy both inequalities: (1) $T>R>P>S$, (2) $2R>T+S$. The payoff matrix is as follows.

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

For simplicity, we set parameters R=1, P=0, S=-0.1 and $T=b$ $(1<b<2)$. Besides, in order to verify the universality of the mechanism in dilemmas of different strength, two parameters D_g $(D_g=T-R=b-1, 0\leq D_g\leq 1)$ and D_r $(D_r=P-S=-S, 0\leq D_r\leq 1)$ are adopted here to depict different dilemma with quantified strengths [25–28]. When both D_g and D_r are positive, the game is a PDG, where D dominates C more favorably when any of both parameters are larger.

In the fields of network evolutionary game theory, various strategy updating rules are proposed, such as best-takes-over updating rule [29,30], so-called best imitation; proportional updating rule [31], updating rule adopting a linear function of payoff difference; and proportional-comparison updating rule with Fermi function [32–35], etc. Generally speaking, the animals in nature tend to observe and imitate more successful one's behavior, which is prime manifestation of social learning. Therefore, best strategy updating rules will be employed in the present model, where individuals will copy the strategy gaining highest payoff in their communities.

Observing human behaviors in society, some individuals who would better cherish the same group ideals for the sake of safety, or for more reward, etc. Despite of different reasons, they either might head away, or stay to confront challenges ahead when there are exploiters in their neighborhood. Considering this, the probability of individuals who may move away is about p in case of being exploited by defectors. Accordingly, with the probability of 1-p, they will stay and learn the strategy which scores highest payoff in last round among direct neighbors. In terms of all cooperators in community, there is no mobility.

The dynamic evolutionary process is simulated by method of Monte Carlo. Theoretically, one time step (t) is defined that each site could be chosen in terms of probability. Firstly, we chose an individual (i) randomly. If there is at least one

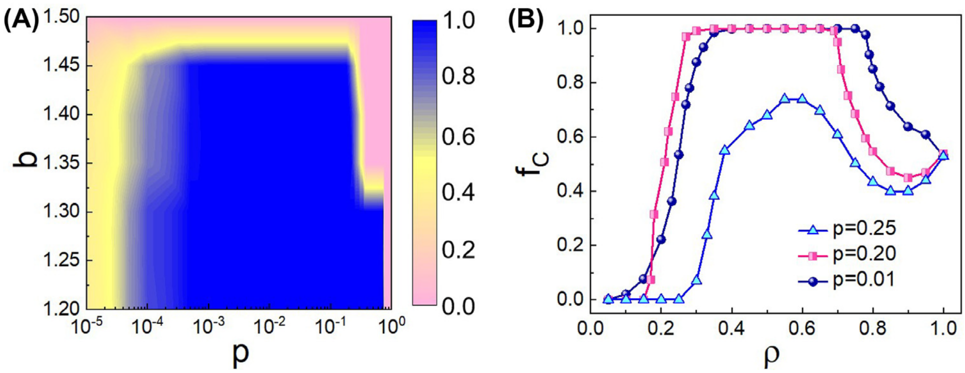

Fig. 1. (color online) Cooperation frequency (f_c) as a function of p and ρ. Color-coded values of f_c in (b, p) parameter space (A), and as a function of ρ for different p (B). The parameters are: $\rho = 0.70$ in panel (A), b=1.45 in panel (B).

defector in his/her community, i will move into a direct empty site with probability p, or update strategy with probability 1-p accordingly. In case of no empty site available, i stays put. In terms of no defectors within community, i will copy the strategy earning highest payoff in his/her community.

In this research, we try to figure out how cooperative behavior diffuses in the system as p changes. Here, the cooperation level of the system is mirrored by the parameter cooperation frequency (f_C), which is calculated by equation $f_C = N_C/(N_C + N_D)$. The parameters N_C and N_D are the number of cooperators and defectors in the lattice respectively. After system evolves into a dynamic equilibrium, each data point in one realization is averaging f_C from t=80,001 to t=10,0000. To avoid the impact of the random initial condition, we run 10 different simulations to obtain the average. Throughout this paper, the parameter M is fixed as 128. Besides, the population density is designated as ρ.

3. Simulation results

We firstly illustrate how moving probability of individuals (p) affects cooperation level of the system. In Fig. 1 (A), we reveal the value of f_c in ($b - p$) parameter space. When p=0.00, the model goes back to a traditional PDG on spatial lattice, where an individual embedded in structured lattices plays games with his/her direct neighbors one by one and learns the strategy gaining highest payoff in her local community. In such case, the dynamical behavior of the system depends on the temptation to defect (b). According to payoff matrix (1), dominating strategy D is unbeatable because of both $T > R$ and $P > S$ in well-mixed population. However, it is observed that f_C fluctuates around 0.24 instead of 0.00 when b=1.45. Be consistent with previous study [29], structured interaction promotes cooperative behavior by enabling cooperative individuals to assort into clusters. Even in the condition of high temptation, a few of cooperators still survive by interacting with other cooperators to receive the benefits of others' cooperation. Interestingly, despite of the same initial situation, the dynamic cooperative behavior is quite different for the case of $p \neq 0.00$. It is shown that cooperation frequency (f_C) could be improved remarkably when p increases for $b \leq 1.45$. Apparently, p plays a key role in affecting cooperation level, especially for the interesting regime $1.3 < b \leq 1.45$. However, the system terminates into a state of no cooperation no matter what p is when $b \geq 1.50$. In panel (B), we also show how f_C evolves with the population density ρ. It is observed that ρ has a wide effective regime to facilitate cooperation level. However, the positive regime becomes narrow and weak as p increases. As intuition might suggested, the essentials of mechanism could be examined in following situation: b=1.45, ρ=0.7.

When interactions are structured, individuals only interact with their network neighbors rather than the whole population. Therefore, it is reasonable and crucial to investigate how spatial clusters evolve dynamically under the same conditions only for different p. In Fig. 2, we present the typical patterns of dynamic evolution for different p. For the sake of comparison, both cooperators and defectors account for half of the total population respectively, who are randomly distributed throughout the whole network with ρ=0.70 initially (Fig. 2A, E and I). In case of p=0.00, it is shown that some tiny cooperative clusters (blue ones) emerge in the red background (defector) when t=200 (Fig. 2B). As time goes by, the figures seem frozen, neither much larger nor much more cooperative clusters are clearly observed (Fig. 2$C - D$). The value of f_C from Fig. 2$A - D$ is 0.50, 0.24, 0.24 and 0.24 respectively. Whereas the spatial patterns are different for $p = 0.01$, a few of much larger cooperative clusters are conspicuous in the ocean of defectors when t=200 (Fig. 2F). Gradually, the number of cooperative clusters increases remarkably versus the time (Fig. 2$G - H$), reaches and keeps a state of dynamic equilibrium when system stabilizes (Fig. 2H). The values of f_C from Fig. 2$E - H$ are 0.50, 0.35, 0.72, and 1.00 respectively. When p increases, e.g., $p = 0.30$, it is observed that a few of larger cooperative clusters appear at $t = 200$, which pales into insignificance when compared with the red ocean of defectors. The values of f_C from Fig. 2$I - L$ are 0.50, 0.27, 0.33, and 0.26 respectively.

Basically, the regions where the strategy competition is fierce, are the borders between two types of clusters. From the standpoint of cooperators in small cooperative clusters, they have much higher per capita frequency of changing decisions for their changeable environment is more unpredictable than those in medium or large clusters. Therefore, individuals in

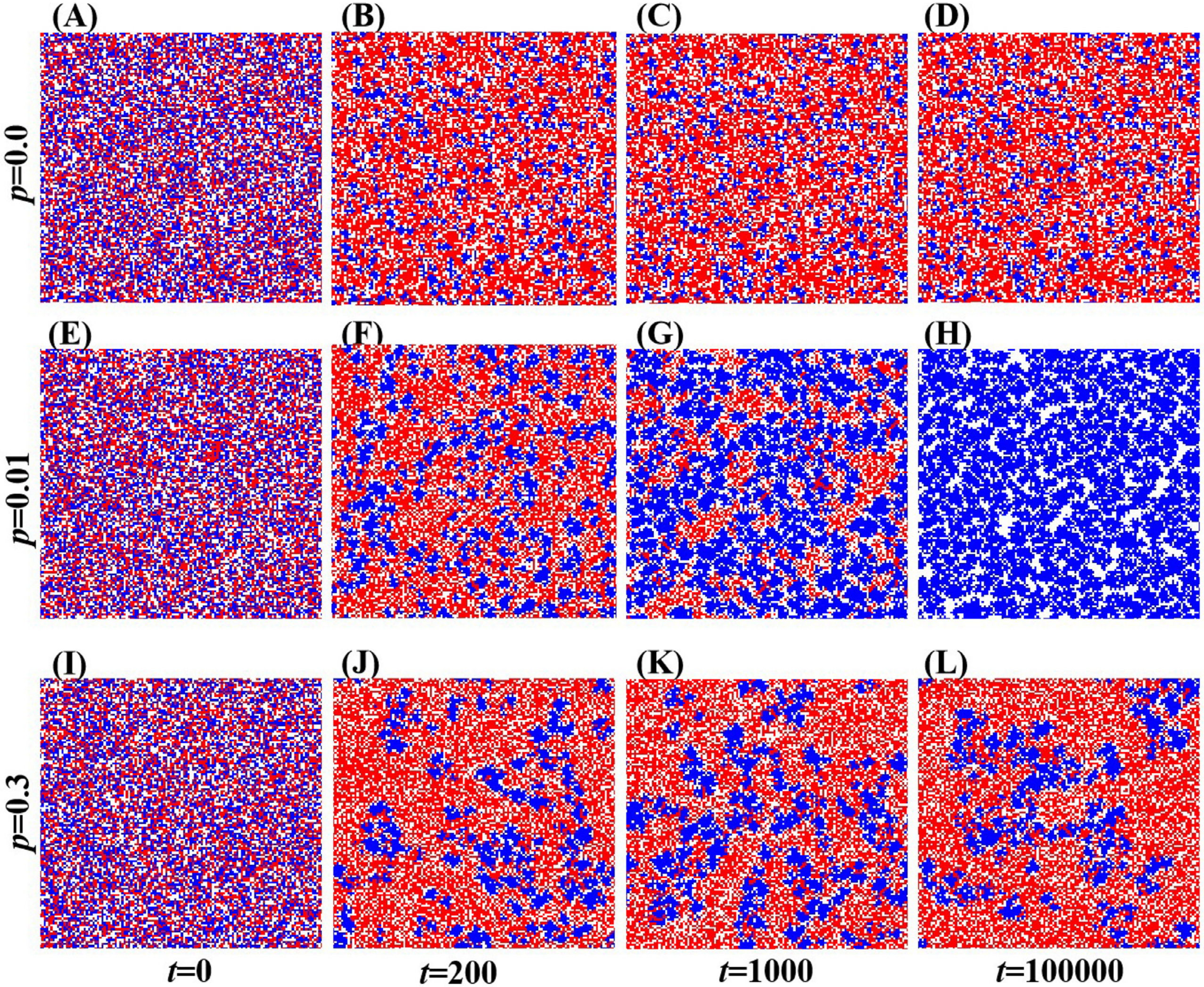

Fig. 2. Evolution of spatial patterns for different network viscosity. The top panels (A-D) shows the dynamic evolution for $p = .00$, the value of f_C is 0.50, 0.24, 0.24 and 0.24 respectively. The middle panels (E-H) for $p = 0.01$, the value of f_C is 0.50, 0.35, 0.72, and 1.00 respectively. The bottom panels (I-L) for $p = 0.30$, the value of f_C is 0.50, 0.27, 0.33, and 0.26 respectively. The color coding is as follows: blue is cooperator, red represents defector, and white is empty site. The initial conditions for different p are the same, that is, 50% individuals are cooperators and 50% individuals are defectors, who are randomly distributed on the whole lattice with ρ=0.70. Other parameter: $b = 1.45$, S=-0.1, P=0.0 and R=1.0.

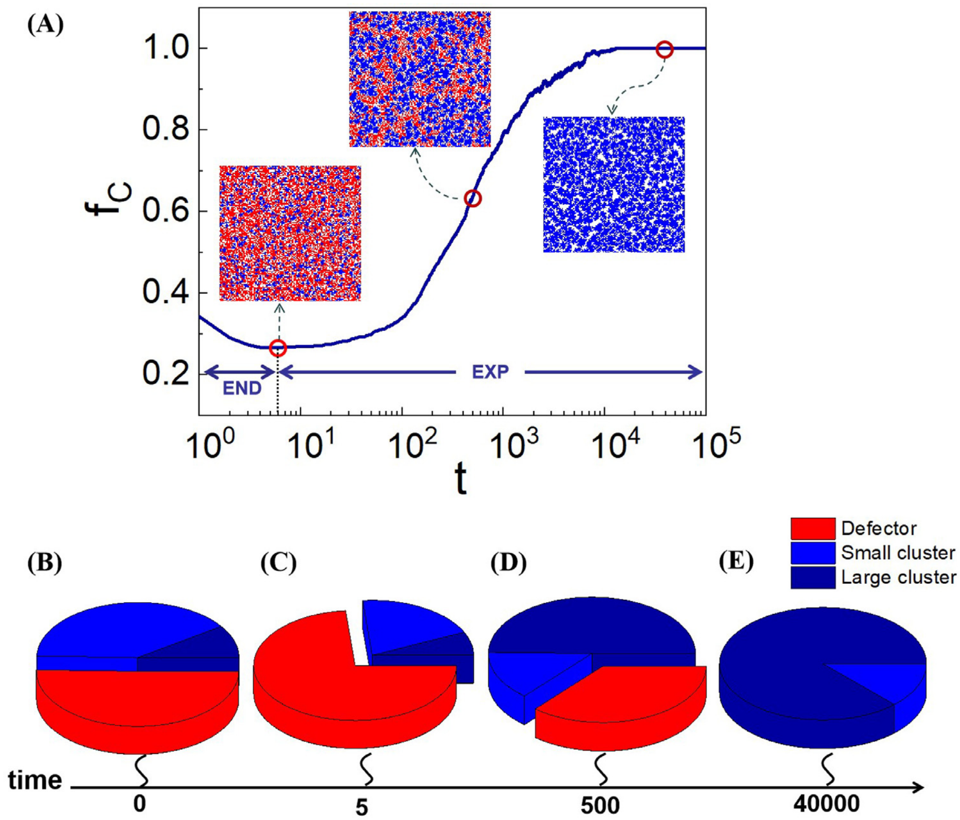

Fig. 3. The time evolution of cooperative clusters for a representative dilemma. Panel(A) depicts the dynamic evolution for D_g=0.4, D_r=0.1. Here, the color coding is as follows: cooperators are in blue, defectors are in red, and empty sites are in white. The key snapshot at t=5, t=500 and t=40000 are shown respectively in this panel, and f_C is 0.27, 0.61 and 1.00 accordingly. Panel (B) depicts the proportion of different cooperative clusters in total cooperative clusters, as well as the proportion of defectors in the whole population at t=0, t=5, t=500 and t=40000 respectively. Here, the average size of cooperative clusters is about 8.82 (λ_{AVG}= 8.82). Thus, the size of cooperative clusters $\lambda \leq 8$ are classified as small ones, and $\lambda \geq 9$ are large ones. Initially, 50% individuals are cooperators and 50% individuals are defectors, who are randomly distributed on the whole lattice with ρ=0.70. Other parameters are b=1.40, p=0.01, S=-0.1, and P=0.0.

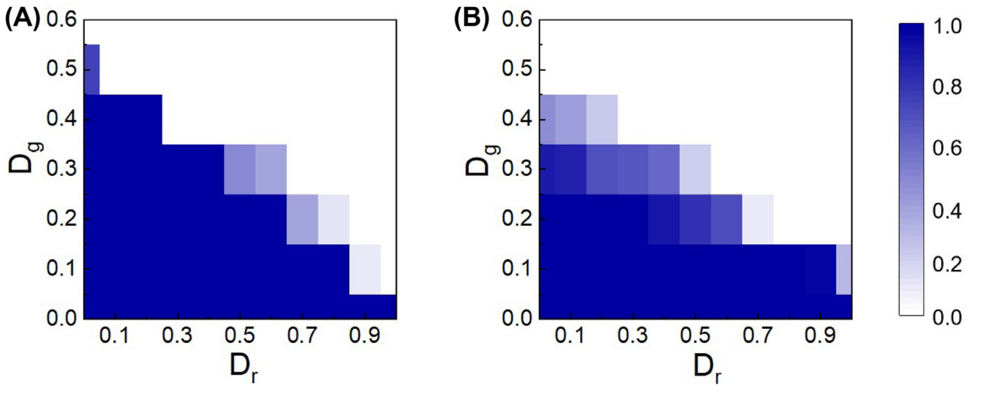

Fig. 4. Color-coded values of f_C in (D_g, D_r) parameter space. $<k>$ =4 (A), $<k>$ =8 (B). Other parameters are p=0.01, ρ=0.70.

small clusters are more active when they suffer constant provocation or invasion from defectors. Particularly in case of p=0 shown in Fig. 2 $A-D$, there is no better choice than forming clusters for cooperators to survive in the absence of effective ways to restrict potential defectors or punish defectors. Apparently, it is hard for cooperative clusters to grow larger or more due to high temptation to defect.

Generally, an empty site may invite either a cooperator or a defector, especially the player in small clusters. A closer observation in Fig. 2 $F-H$, it is found that the distributions of empty sites locating in cooperative clusters is different from that in defecting neighborhoods. Comparing with the situation that empty sites are sprinkled evenly over defecting

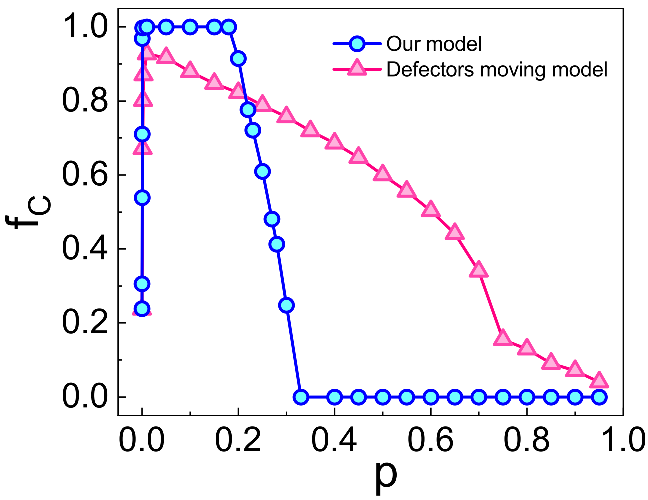

Fig. 5. Cooperation frequency (f_c) as a function of p for different mobility mechanisms. In order to compare with current model, we introduced another model, where defectors move away. Other parameter: $b = 1.45$, ρ=0.70.

neighborhood, most of empty sites in dense cooperative clusters concentrate at the boundaries. The cooperative clusters are stable for following three reasons. Firstly, there is barely any chance for defectors to invade or destroy dense cooperative clusters, where there are few empty sites. Secondly, there is little prospect of seeing that cooperator either move away or alter their strategies by social learning (They are sealed off by cooperative team, sharing equal payoffs). Last but not least, the cooperators at the boundaries between two kind of neighborhoods gain higher payoff than defectors, which favor the cooperative clusters grow larger.

Actually, it is more like a punishment for defectors that individuals would rather move away than staying and interacting with them. Without interaction, how payoff comes? As a punishment, alienation from defectors favors cooperation. Therefore, the cooperative clusters in cases of “moving away from defectors” (both the middle and bottom patterns) are larger than the case of “never move” (top patterns). However, the effect on cooperation is not in direct proportion to p. In terms of p=0.30, the number of cooperative clusters declines despite of large cooperative clusters. Low probability of mobility guarantees the probability of future encounter, which means players could cooperate with each other and survive by direct reciprocity. However, as p grows, the probability of mobility increases, which increases the random mixing and gets system closer to the mean field situations, where defectors dominates theoretically. High mobility decrease the probability of a future encounter, which counteracts the impact of direct reciprocity.

Furthermore, the dynamic evolution of cooperative clusters is also investigated using the concepts of END (Enduring period) and EXP(Expanding period) [5]. END is the episode of cooperative clusters surviving from the initial random and chaotic state. With this, it is the EXP episode if these cooperative clusters grow larger by taking over defecting neighborhood. Or its time evolution terminates in END instead of shifting into EXP. As is shown in Fig. 3, initially, all individuals are randomly distributed over the whole lattice with ρ=0.70. Here, about two-thirds of cooperators are in small clusters (B). In panel (A), as time goes by, the number of cooperators shrinks fast as defectors keep invading before t=5. Only a few of cooperators successfully survive through the formation of compact clusters at t=5. Particularly at the end of END episode, almost half of cooperators in small clusters perish and be taken over by defectors due to fierce competition (C). Afterward, these cooperator in compact cooperative clusters counterattack and recapture lost territory, further spread to defectors neighborhoods (D). In EXP episode, it is shown that cooperators in large clusters play a key role in winning back lost ground and further extending into defecting neighborhood (E).

For the sake of the potency of promoting cooperation, it is interesting to figure out what dilemmas, where the mechanism could still enhance cooperation effectively. And the results are shown in Fig. 4(A). Considering the potential impact of the node degree, we also consider the lattice having a relatively more links, such as $<k>$=8 (Moore neighbors) (B). Either D_g or D_r grows, the strength of dilemmas rises. The large D_g increases higher temptation to defect. The large D_r results in severe loss of cooperators. It is shown that the applicable scope where the mechanism could work out of a dilemma is the triangle area of diagonal between D_g=0.5 and D_r=1.0. It is worth mentioning that f_C is almost close to 1.00 as long as the mechanism is effective. Results similar to these are found when individuals interact with eight nearest neighbors instead of four nearest neighbors, as shown in panel (B). By and large, these two panels present the same shape, but for slight differences of color shade. In short, the above results seem robust on regular networks with different node degrees. In case of small D_g and D_r, the similar results are also found in the mechanism, where a pair-wise Fermi update rule is adopted.

Actually, the mobility is driven by the fact that there is a defector in the community. Consider the misgiving that one rotten apple spoils the barrel, how it comes if defectors are driven to move away. Now, we compare these both mechanisms. The results are shown in Fig. 5. It is interesting to find that f_C of different mechanisms have similar trends, which implies that dynamical behavior of the system depends on low mobility. In fact, either moving away to refuse to interact with defectors, or driving defectors away to deprive their interactions is a punishment for defectors. No interactions, no gains. However, the large probability of mobility may counteracts the impact of direct reciprocity. Therefore, alienation from defectors is conducive to cooperation provided the network reciprocity still works.

4. Discussion

Mobility has being investigated for several decades, which keeps offering interesting surprises. In this paper, we proposed a simple yet universal model, where individuals with defectors in their communities have both ways to alter their situations, either moving away with probability of p or updating strategies with 1-p accordingly.

Simulation results revealed that the size of cooperative clusters in mobile population are larger than the case “never move”, which signifies that the moving away from defectors is conducive to form large cooperative clusters. Whereas the number of large clusters relies mainly on the parameter p. Low mobility could create an interaction network with high viscosity, where direct reciprocity works. However, high mobility increases the random of mixing, extends the range of interaction, and brings the system close into a random interaction network, which weakens the positive effect of direct reciprocity on cooperation. Neither alienation from defectors only nor direct reciprocity only can promote cooperation as effectively as their combination does. Our results may also have application in vaccination dilemma of epidemic spreading [36], where a joint policy of quarantine and isolation is an efficient way for epidemic control in the condition of high disease spreading rate [37].

Similar results are also found in the experiment work [20], where subjects are allowed to update their social network connections dynamically. Compared with fixed network (never move) and random network (high mobility), dynamic connections (with low mobility) can stabilize cooperation in groups. But the viscosity of the connections facilitating cooperative behavior is lower in our model. Obviously, there are actual gaps between experiments and theoretical models, such as the population size, the imitation rules, etc. Particularly, the effects on cooperation of the same mechanism only with different imitation rules could be quite different.

Despite of available and accessible information for normal individuals, how to extract useful information and knowledge from large amounts of data seems not easily achieved. However, it is easy for an individual to acquire the information whether there is a defector in his/her neighborhood just by comparing his/her own payoff with the expected payoff. Due to the big expense for mobility, the individuals suffering defectors may reluctant to move away. Our results show that only 1% of individuals (minorities) being exploited could brave the situation and alienate from them voluntarily, and the cooperative behavior among whole population could be promoted effectively via the limited mobility of minorities. Comparing with the cost of mobilizing whole population to cooperate by either punishing defectors or rewarding cooperators, limited mobility away from defectors could spare public resource effectively.

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