PHYSICAL REVIEW E **80**, 046109 (2009)

Cooperation enhanced by moderate tolerance ranges in myopically selective interactions

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(Received 15 May 2009; published 14 October 2009)

We present a mode of myopically selective interaction to study the evolutionary prisoner's dilemma game in scale-free networks. Each individual has a reputation-based tolerance range and only tends to interact with the neighbors whose reputation is within its tolerance range. Moreover, its reputation is assessed in response to the interactions in the neighborhood. Interestingly, we show that moderate values of tolerance range can result in the best promotion of cooperation due to the emergence of group selection mechanism. Furthermore, we study the effects of weighting factor in the assessment rule of reputation on the evolution of cooperation. We also show how cooperation evolves in some extended situations, where an interaction stimulus payment is considered for individuals, and where the strategy and reputation of individuals can spread simultaneously. Our results may enhance the understanding of evolutionary dynamics in graph-structured populations where individuals conditionally play with their neighbors according to some myopic selection criteria.

DOI: 10.1103/PhysRevE.80.046109 PACS number(s): 89.75.Da, 87.23.Kg, 02.50.Le

I. INTRODUCTION

Understanding the emergence and maintenance of cooperative behavior is a fascinating, yet challenging direction in evolutionary biology [1]. Evolutionary game theory has become a powerful framework to study the evolution of cooperation among competing individuals. In particular, the prisoner's dilemma game (PDG) is one of the most widely applicable games for this purpose [2]. Traditionally, the evolutionary PDG is studied in an infinite, well-mixed population, where all individuals are equally likely to interact with each other, but unfortunately cooperation cannot emerge whenever evolution under replicator dynamics [1].

Such an unfavorable well-mixed scenario for cooperators in the PDG has stimulated the study of cooperation in more realistic situations. Noticeably, considerable attention has been shifted into graph-structured populations. Evolutionary graph theory provides a natural and reasonable framework for this approach: each individual occupies a vertex and is constrained to play with its immediate neighbors along the edges. Taking into account these simplifying settings, Nowak and May seminally proposed the spatial PDG model. They found that such spatial structure allows cooperators to build clusters to resist exploitation by defectors, thus enabling cooperation to be sustained [3]. Following this pioneering work, much effort has been expended on studying the evolution of cooperation in more complex topologies (see Ref. [4] and references therein), such as small-world and scale-free networks. In particular, Santos *et al.* pointed out that scale-free networks can provide a unifying framework for the emergence of cooperation [5–7]. Subsequently, it is found that the strong heterogeneity of the degree distribution is identified as the main driving force behind the flourishing cooperative behavior in scale-free networks [8,9]. Recently, Perc found that cooperation on scale-free networks is extremely robust against random deletion of vertices but declines quickly if vertices with the maximal degree are targeted [10]. This work supplements previous studies examining the evolution of cooperation on scale-free networks, and further shows the importance of the degree distribution heterogeneity for the evolution of cooperation by random and intentional removal of vertices.

Furthermore, some other factors in the framework of graph-structured populations have been considered, such as stochastic noise in payoffs and updating rules [11–13], inhomogeneous teaching activity [14,15], preferential selection [16], imperfect imitation [17], evolving learning rules [18], asymmetric interaction and replacement graphs [19–21], individuals' mobility (migration) [22–27], and social diversity [28–30]. These examples of alternative ways have been demonstrated as potential promoters of cooperation with noticeable success, and can be justified from the viewpoint of real society.

It is worth noting that most previous approaches simply assume that individuals always deterministically interact with all their neighbors. Indeed individuals do not always play with others by using this interaction mode in the real society. Far less attention has been paid to different interaction modes as a possible alternative. Remarkably, some recent studies introduced a simple mode of interaction, stochastic interaction, instead of deterministic interaction to study evolutionary games [31–34]. Under the framework of evolutionary graph theory, it is found that different evolutionary dynamics can emerge in the mode of stochastic interaction. In particular, such stochastic interaction is found to be a potential promoter of cooperation in the spatial PDG [32,33]. These results enrich our knowledge of evolutionary dynamics in nature, and meanwhile enlighten us to propose different more realistic ways of interaction for further study.

At present, we propose an alternative mode of myopically selective interaction, conditional interaction, into graph-structured populations. Our starting point is realizing that, in the real society individuals would conditionally participate in

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the interactions based solely on their own myopic selection criteria. As a phenotypic feature, reputation can be used to help individuals recognize "good and bad guys" [4] and has been used as a selection parameter to help individuals adjust their partnerships [35]. From the viewpoint of the usage, reputation could be also used to help individuals carry out the myopically selective interactions. Furthermore, social tolerance is found to be a major factor that permits other people's free participation [36]. In human society, some people not only play with the ones with higher reputation, but also play with the ones with lower reputation. In this sense they myopically play with others. Nevertheless, they generally have a certain tolerance range, and do not tend to play with the ones whose lower reputation is beyond the tolerance range. In view of these facts, we can consider this reputation-based tolerance range to carry out conditional interactions for neighboring individuals. Specifically, each individual has a reputation-based tolerance range, and only prefers to interact with the neighbors whose reputation is within its tolerance range. For each pair of individuals, they both behave in such myopically selective manner toward the other one, similar to the mutual selection rule (e.g., for business transactions) in the real life society. Thus, both parties can interact with each other only when their reputation scores are within each other's tolerance range. It is worth noting that individuals would easily interact with neighbors with a similar reputation, due to the mutually myopic selections. Moreover, individuals' reputation is used to help them to choose interaction partners. Hence the usage of reputation here is distinct from previous reputation-based studies [37–39] where individuals using conditional strategies engage in compulsory pairwise interactions: they take into consideration the reputations of their opponents, only when they decide to cooperate or to defect.

In general, an individual's reputation could be a continuous variable, which should depend on the previous and current performances [35,37–39]. Here we consider that cooperation can increase the reputation, partially inspired by the work of Nowak and Sigmund [37]. In addition, as we notice that in human society, people can generally get higher reputation if they help more other people. In games on graphs [3], each individual simultaneously engages in several pairwise interactions by using the same strategy. Hence the reputation of individuals in the graph-structured populations should also depend on the number of pairwise interactions. Furthermore, individuals do not always engage in pairwise interactions with all their neighbors at each generation in our model, and different individuals have different numbers of average neighbors in real graph-structured populations [4–6]. Therefore, to provide a universal framework to assess players' reputation, or to weaken the effects of degree heterogeneity on players' reputation, the number of pairwise interactions should be normalized in the assessment rule. In reality, when these above factors are incorporated into the definition of reputation, a strategy nonpreferential reputation updating is implemented and individuals can make use of more precise reputation information to engage in the conditional interactions.

In this study, we aim to explore how the conditional interaction depending on the reputation information and tolerance range influences cooperative behavior in social networks, and mainly concentrate on the present model in evolutionary PDG on scale-free networks. Interestingly, by using Monte Carlo simulations we demonstrate that such conditional interaction can enhance cooperation, and moderate values of tolerance range can result in the best promotion of cooperation. In the rest of this paper, we will first describe our model, next present the results and discussion, and finally draw our conclusion.

II. MODEL

We consider the evolutionary PDG in the Barabási-Albert scale-free networks [40]. Each individual who occupies one site of the network can only follow two simple strategies: cooperate (C) and defect (D). Following previous studies [41,42], we adopt the rescaled payoff matrix depending on one single parameter,

$$\begin{array}{c} \\ C \\ D \end{array}\begin{array}{c} \begin{array}{cc} C & D \end{array} \\ \begin{pmatrix} 1 & 0 \\ 1+r & r \end{pmatrix} \end{array}, \tag{1}$$

where $r=c/b$ represents the cost-to-benefit ratio.

During the stage of interaction, each player i tends to interact with one neighbor j if player j's reputation is within the tolerance range of player i, that is, $R_i-h\le R_j$. Similarly, player j tends to interact with player i if player i's reputation is within the tolerance range of player j, that is, $R_j-h\le R_i$. As a result, for paired players i and j, they can interact with each other if $|R_j-R_i|\le h$, where R_i (R_j) is the reputation score of player $i(j)$, and h is the tolerance range of players i and j. For simplicity, we assume that each player has the same tolerance range in this study.

According to this mode of conditional interaction, player i engages in pairwise interactions within its neighborhood, and then collects its payoff P_i as

$$P_i = S_iI_c + (1-S_i)[I_c(1+r) + (k_I - I_c)r], \tag{2}$$

where k_I is the number of player i's interaction partners, I_c is the number of cooperators among the interaction partners, and S_i denotes player i's strategy [$S_i=1$ for C; $S_i=0$ for D].

After playing the games, each player's reputation score needs to be assessed. Specifically, we allow each player's reputation score to be updated every generation as a weighted average of its previous score of reputation and its immediately preceding experience with its interaction neighbors. The reputation score of player i at time t is thus

$$R_i(t) = (1-\alpha)R_i(t-1) + \alpha S_i(t)\frac{k_I}{k_i}, \tag{3}$$

where $0<\alpha<1$ is a weighting factor, $R_i(t-1)$ is the reputation score of player i at time $t-1$, and k_i means the connectivity of player i. Here, $S_i(t)\frac{k_I}{k_i}$ is a measure of player i's experience with k_I interaction neighbors when using strategy $S_i(t)$ at time t.

Subsequently, players will update their strategies according to the updating rule compatible with the replicator dynamics (RD). Specifically, player i randomly selects one

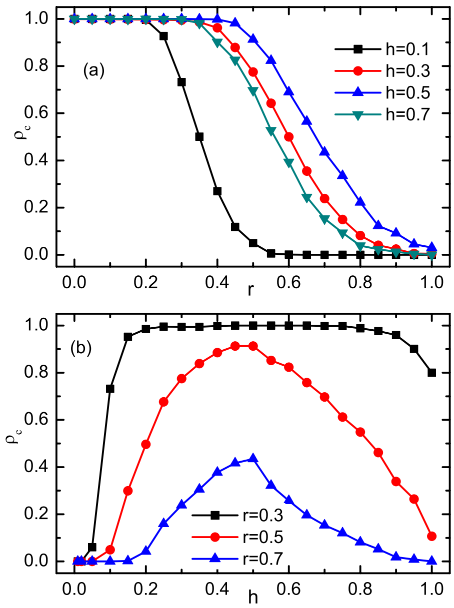

FIG. 1. (Color online) Evolution of cooperation. (a) Fraction of cooperators as a function of r for different values of h. (b) Fraction of cooperators as a function of h for different values of r. α is set to 0.5, and each data point reported here results from over 10^3 different realizations.

player j from its adjacent neighbors. If $P_i < P_j$, i will adopt j' strategy with a probability depending on the payoff difference,

$$W = \frac{P_j - P_i}{M},$$

where M ensures the proper normalization and is given by the maximum possible difference between the payoffs of i and j.

In this model, each individual is initially assigned a reputation score randomly chosen in the interval [0,1], and correspondingly its continuous reputation score varies between 0 and 1. Thus, in this study we set $0 < h < 1$. In what follows, we mainly focus on at what values of tolerance range cooperation may thrive, i.e., the effects of h on the evolution of cooperation.

III. RESULTS AND DISCUSSION

Simulations are carried out for a population of players with size $N = 10^3$ occupying the nodes of scale-free networks with average degree $z = 4$. Initially, the two strategies of C and D are randomly distributed among the population with an equal probability. Individuals' reputation scores are randomly distributed within the interval [0,1]. In our study, we implement this computational model with synchronous update [43], and the cooperation level is obtained by averaging over 2×10^3 generations after a transient time of 2×10^4 generations [44].

Figure 1(a) shows the cooperation level ρ_c as a function of r for different values of h. One can see that the cooperation level monotonously decreases as the value of r increases, for

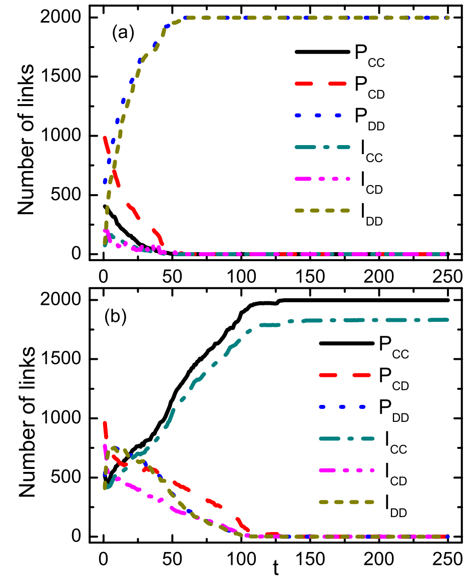

FIG. 2. (Color online) Time evolution of the numbers of paired (P_{CC}, P_{CD}, and P_{DD}) and interaction (I_{CC}, I_{CD}, and I_{DD}) links for different values of h: (a) $h = 0.1$ and (b) $h = 0.5$. r and α are both set to 0.5, and the data shown here are obtained in one realization.

each value of h. Interestingly, for some fixed r, e.g., $r = 0.6$, we notice that there may exist some intermediate values of h leading to the optimal cooperation level. To qualify the effects of h on the evolution of cooperation more precisely, we study ρ_c as a function of h for various r in Fig. 1(b). Clearly, one can find that for small values of r, there exist some moderate values of h, resulting in a plateau of high cooperation level. With increasing the value of r, the length of the high cooperation plateau decreases. Finally for large $r > 0.4$ [see Fig. 1(a)], the plateau of high cooperation level vanishes, and there exists a moderate level of h around 0.5, resulting in the most favorable cooperation level. These results show that this mode of conditional interaction favors the emergence of cooperation, and cooperation can be best promoted at moderate values of reputation-based tolerance range.

The nontrivial dependence of ρ_c on h can be understood in the following way. For $h \to 1$, each individual interacts with its neighbors with little restriction, and our model could recover the traditional study in scale-free networks [5]. For high r, by interacting with other cooperators, defectors can exploit more and more elements of the cooperator core's outer layer, and finally dominate in the system [9]. On the other hand, for small h defectors can interact with most of their defective neighbors due to their low reputation scores. Whereas most of neighboring cooperators cannot help each other due to their different reputation scores [see Fig. 2(a)]. It means that the small values of h smite the interactions between cooperators more efficiently. As a result, cooperators can be wiped out by defectors finally. While for intermediate h, some neighboring cooperators' reputation differences are smaller than the value of h, thus they can interact with each other. This induces a positive feedback mechanism, which makes the interactions between cooperators grow larger and stronger [see Fig. 2(b)]. Moreover, defectors are hindered to interact with some cooperative neighbors, although they are not hindered to interact with their defective neighbors [see Fig. 2(b)]. In this situation, positive assortment between cooperators can be generated [2], and defectors become vulnerable to cooperators. Thus cooperation can evolve and prevail in the population.

It is important to note that the system could reach an absorbing state in scale-free networks after a suitable transient time when h is not large (see Fig. 2). During the evolutionary process the interactions between cooperators and defectors could be inhibited, especially for small h. Here, we would like to emphasize that the segregation of cooperator-cooperator and defector-defector interactions occurs spontaneously over time via the strategy nonpreferential reputation updating, which is not introduced directly in our model. Thus we show a mechanism that reproduces a feature that is frequently observed in reality based on the reputation of players. Furthermore, defectors (cooperators) do not only interact with their defective (cooperative) neighbors. Cooperative individuals do not necessarily play with all their cooperative neighbors even if all individuals choose to cooperate [see Fig. 2(b)], which further shows that the mode of conditional interaction is myopic. From these features, we conclude that there are different reputation scores maintained in the population during the evolutionary process. Defectors will obtain a low reputation score as time increases, but cooperators will not necessarily obtain a high reputation score even when the absorbing state of full cooperation is reached. These may reflect the phenomena about the inhomogeneity and segregation of people's reputation scores in the real society. Thus the reputation information can differentiate the players, and can be seen as a kind of tag [4] which helps individuals using unconditional strategies choose the interaction partners according to the myopic selection. Due to the mutually myopic selections, neighboring individuals would easily interact with each other if they have similar reputation scores. Hence the action rule based on reputation in our model is different from indirect reciprocity based on reputation where individuals with high reputation are more likely to receive help from others [37–39].

In combination with the above points, we argue that defectors are hindered to play with cooperative neighbors with high reputation for moderate values of tolerance range. At the same time these cooperators could play with some others with the same strategy. This is basically a sort of group selection mechanism emerging spontaneously in this mode of myopically selective interaction. In this situation, cooperators whose degree belongs to the high-degree class (e.g., $k_{max}/3 \leq k \leq k_{max}$, see similar definition of the high-degree class in Refs [29,45].) can easily sustain and spread their strategy even for high r [9]. Thus, the cooperator density among all the nearest neighbors of players having high degree increases gradually as time increases (see ρ_c^{hn} in Fig. 3), and finally the absorbing state of full cooperation could be reached (see ρ_c in Fig. 3). From the viewpoint of these emergent features about the time evolution of cooperative strategy, the working mechanism responsible for the promotion of cooperation in our model is conceptually similar to the one reported recently by Szolnoki and Perc [46], who found that the slow addition of new links within the framework of evolving graphs leads to the emergence of group selection mechanism, resulting in the gradual increase of the cooperative domains around players with high degree, and the final state of full cooperation.

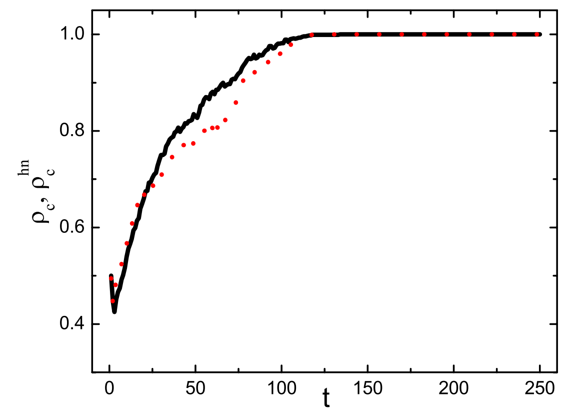

FIG. 3. (Color online) Time evolution of ρ_c (solid black line) and the fraction of cooperators among all the nearest neighbors of high-degree players ρ_c^{hn} (dotted red line) obtained for $h=0.5$, $r=0.5$, and $\alpha=0.5$. The data shown here are obtained in one realization.

Figure 4 shows the cooperation level in dependence on h for different values of α. Noticeably, one can clearly observe the nonmonotonous dependence of ρ_c on h for each value of α. In addition, for small tolerance range the cooperation level can be higher at modest values of α; while for large tolerance range the cooperation level can be higher at large values of α. In reality, the weighting factor α introduces a memory effect on reputation adjustment [35]. For small α, individuals' reputation mainly relies on the historical performance, and a rapid feedback mechanism cannot be provided between the current interaction performance and reputation adjustment, which can induce reputation differences between neighboring cooperators. In this case, the interactions between cooperators are presumably more unfavorable especially for small h, and thus cooperation would be weakened (e.g., for $\alpha=0.1$ in Fig. 4). For large α, individuals' reputation mainly relies on the current performance. Although a rapid feedback mechanism can be at work between the current interaction performance and reputation adjustment, the different fractions of pairwise interactions in the neighbor-

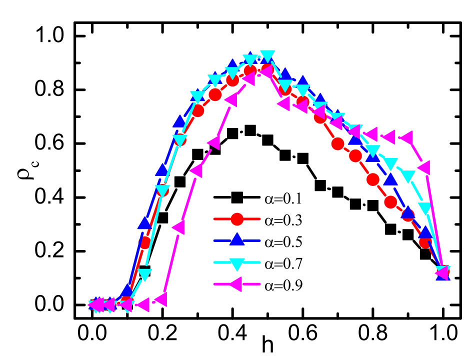

FIG. 4. (Color online) Fraction of cooperators as a function of h for $r=0.5$ and different values of α. The results are averages taken over 10^3 different realizations.

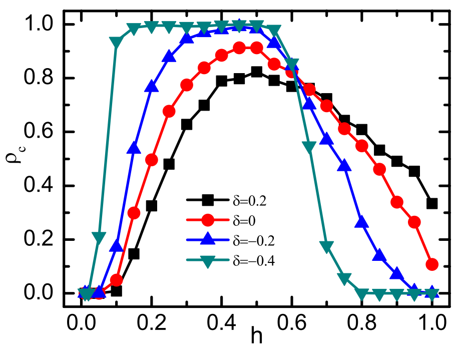

FIG. 5. (Color online) Fraction of cooperators as a function of h for different values of δ. Here, $\alpha=0.5$, $r=0.5$, and each data point is obtained by averaging over 10^3 different realizations.

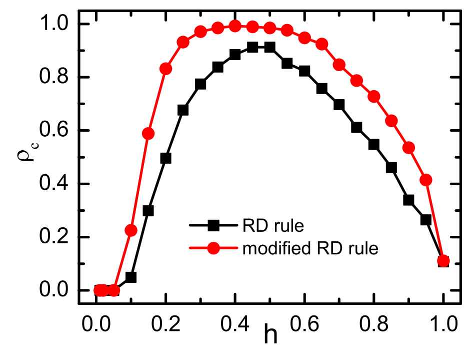

FIG. 6. (Color online) Fraction of cooperators as a function of h under the RD rule and modified RD rule. Here, $r=0.5$, $\alpha=0.5$, and results correspond to averages over 10^3 different realizations.

hoods still induce reputation differences for neighboring cooperators. As a consequence, cooperation would be inhibited when tolerance range is small. While for large h the interactions between cooperators are little restricted, thus promoting cooperation (e.g., for $\alpha=0.9$ in Fig. 4).

Finally, we take into account some interesting extensions after presenting main results of the original model. Previous work has reported that participation costs dismiss the advantage of heterogeneous networks in the evolution of cooperation when the participation is compulsory [47]. How do participation costs influence the evolution of cooperation in scale-free networks when the participation is conditional? To do this, we consider that each individual can receive an additional constant stimulus payment δ when interacting with one neighbor. Correspondingly, the final total payoff of player i at each generation can be given as

$$P_i = S_i I_c + (1 - S_i)[I_c(1 + r) + (k_I - I_c)r] + k_I \delta.$$

Here, the stimulus payment $\delta > 0 (\delta < 0)$ characterizes the interaction reward (cost). In Fig. 5, we present the cooperation level in dependence on h for different values of δ, and find that there still exist intermediate values of h resulting in the best promotion of cooperation, for each value of δ. More interestingly, we find that for $h < 0.6$, the cooperation level decreases as δ increases; while for $h > 0.6$, the cooperation level increases as δ increases. These results can be understood in the following way. For small h, the interactions between neighboring defectors are not inhibited, whereas the interactions between neighboring cooperators are inhibited. Hence, the interaction cost (reward) can weaken (strengthen) the advantage of defectors in collecting payoffs, which results in the promotion (inhibition) of cooperation. Whereas for large h, there is little restriction for the interactions between neighboring individuals. Thus the interaction cost (reward) can dismiss (enhance) the advantage of degree heterogeneity of scale-free networks in the evolution of cooperation, which is consistent with previous results [47]. Moreover, it is worth noting that the advantage of degree heterogeneity of scale-free networks in the evolution of cooperation could be also weakened by normalizing the total payoff [45,48,49]. In our present framework, we have checked that there still exists the nontrivial dependence of cooperation level on tolerance range when the total payoff is normalized.

We also consider a modified RD rule in the present interaction mode, and assume that in each time step each player is replaced by one randomly chosen neighbor with the probability W. In other words, the strategy and reputation of individuals can be simultaneously imitated under the updating rule. Results about the comparison between these two rules are reported in Fig. 6, which shows that cooperation can be better promoted under this modified RD rule. In reality, this modified RD rule can enhance the reputation spreading of cooperators who obtain high payoffs, resulting in the emergence of more powerful group selection. Naturally, the cooperation level can be more favorable.

Furthermore, we investigate this mode of conditional interaction for different initial frequencies of cooperators, and still observe the nontrivial dependence of ρ_c on h (that is, intermediate values of h can lead to the optimal cooperation level). More importantly, we test the mode of conditional interaction in other typical network structures, i.e., regular, random, and small-world networks, and also find that the similar dependence of cooperation level on h. It could be concluded that moderate values of tolerance range in this conditional interaction mode can result in a robust promotion of cooperation in social networks.

IV. CONCLUSION

In summary, we have presented a mode of conditional interaction into the evolutionary PDG, in combination with individuals' reputation and tolerance range. We have shown that such myopically selective interaction can lead to the emergence of group selection mechanism, resulting in the optimal cooperation level at moderate values of tolerance range in scale-free networks. Moreover, we found that the nontrivial dependence of cooperation level on tolerance range does not qualitatively change for different values of weighting factor. We further observed that moderate values of weighting factor are better for the evolution of cooperation when tolerance range is small; while high values of weighting factor are better for the evolution of cooperation when tolerance range is large. When the interaction stimulus payment is considered for individuals in the present framework, we found that the cooperation level increases with increasing the value of stimulus payment for large tolerance range; while the cooperation level decreases with increasing the value of stimulus payment for small tolerance range. In addition, we found that cooperation can be better promoted in the modified RD rule where strategy transfer and reputation transfer can be both allowed. We also found that moderate values of tolerance range can still result in the optimal cooperation level on other network topologies. Our work may provide an alternative way to promote cooperation in graph-structured populations, and the present framework can be used in other problems where agents can selectively participate in the social interactions.

ACKNOWLEDGMENTS

We are grateful to three anonymous referees for their constructive comments and suggestions which are helpful in improving our manuscript. We thank M. Doebeli and A. Blachford for helpful discussions about this model. X.C. gratefully acknowledges the support from China Scholarship Council (Grant No. 2008100772). This work was partially supported by National Natural Science Foundation of China (NSFC) under Grants No. 60674050, No. 60736022, and No. 10972002; National 973 Program (Grant No. 2002CB312200); National 863 Program (Grant No. 2006AA04Z258); and 11-5 project (Grant No. A2120061303).

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