

Emergence of cooperation through coevolving time scale in spatial prisoner's dilemmaZhihai Rong,^{1,*} Zhi-Xi Wu,^{2,†} and Wen-Xu Wang^{3,‡}¹*Department of Automation, Donghua University, 201620 Shanghai, China*²*Department of Physics, Umeå University, 901 87 Umeå, Sweden*³*Department of Electrical Engineering, Arizona State University, Tempe, Arizona 85287, USA*

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We study evolutionary prisoner's dilemma game by considering adaptive strategy-selection time scale among individuals according to a “win-slower, lose-faster” rule: if an individual successfully resists the invasion of an opponent, she is prone to hold her strategy for longer time through decreasing her strategy-selection time scale; otherwise, she increases the time scale because of losing. We find that the greater the losers increase their strategy-selection time scales, the better for cooperation. Interestingly, optimal cooperation can be induced by proper adaptive rate in the strategy-selection time scale. Our results may have potential implications in the design of consensus protocol in multiagent systems.

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I. INTRODUCTION

Evolutionary game theory provides a powerful framework for understanding ubiquitous cooperative behaviors existing in biological, social, and economical systems [1–4]. The prisoner's dilemma (PD) game is one of the most famous paradigms to depict the conflict between two selfish individuals [5]: mutual cooperation can provide a positive income for both players, while a greedy individual is prone to defect to gain higher payoff regardless of the punishment to her cooperative opponent. This egoistic behavior leads to a tragedy that the individuals are trapped in the scenario of mutual defection where who first switch to cooperation strategy will be punished.

One of the promising mechanisms to escape the dilemma is the combination of interaction structure, or spatial (or networked) reciprocity [6–9] with evolutionary games. The interaction structure of the individuals can be represented by a network, which describes who plays games with whom, and who learns from whom as well. Quite recently, a number of investigations have been carried out to uncover nontrivial effects of topological properties on the maintenance of cooperation [10–20]. In the general framework of spatial (network) games, players compete with each other according to “Darwinian selection” rule, i.e., the strategies leading to higher fitness are usually imitated, where the fitness is simply determined by relevant payoffs. So far, in this framework, many factors that play important roles in the game dynamics have been discovered, such as noise [20], similarity [21], preferential selection [22], memory effect [23], payoff aspiration [24], imperfect imitation [25], asymmetric cost [26] and so on. Some interesting dynamical phenomena have been observed, such as directed percolation [10], resonance-like behaviors [27,28], hysteresis loops [29], etc. Recently, Szolnoki *et al.* systematically studied the teaching ability that depict the heterogeneous influence of strategy transfer capa-

bility of individuals, and found the heterogeneity of teaching activity can support cooperation [30–34]. The presence of diversity of social status [35] and rationality [36] is also found to facilitate cooperation. Furthermore, the permission of players to adaptively select interaction neighbors [37–42] or migrate [43–45] can suppress the spreading of defection and thus favor cooperation (seeing [46] for a survey).

In general, there are two time scales in the game dynamics, one is interaction time scale—which characterizes how frequently the individuals interact with each other, and the other is strategy-selection time scale—which depicts how frequently they modifies their strategies. Most previous researches assume the two time scales are identical, i.e., the individuals immediately update their strategies after one round of game. However, Roca *et al.* found that if the two time scales are nonidentical, the final evolutionary results can change dramatically compared to identical cases [47]. In a recent work, Wu *et al.* studied the diversity of reproductive time scale on the evolution of cooperation, and found that a proper relationship between the two time scales can best support cooperation [48]. In the present work, we extend the work in [47,48] by considering adaptive strategy-selection time scale for the individuals. Individuals can tune their strategy-selection time scale according to the “win-slower, lose-faster” rule: if an individual defeats her opponent with a different strategy, she is willing to extend the lifetime of current strategy by decreasing her strategy-selection time scale. Otherwise, she will increase her time scale to seek better strategy. Our investigation shows that tuning time scale with proper adaptive rate will promote the long-term cooperative clusters and boost the maintenance of cooperation. Since adaptivity is a generic property of complex adaptive systems, we believe such consideration would gain more instructive insights in understanding the evolution of cooperation in real world.

In the following section, we define our evolutionary PD model. In Sec. III, we present our numerical results and analysis. Finally, in Sec. IV we draw our conclusion and make some discussions.

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II. MODEL

Each individual i locates on one site of a regular 100×100 square lattice with periodic boundary conditions, and can be either unconditional cooperator (C) or defector (D). The PD games are played among connected neighbors. If two individuals cooperate with each other, both of them receive the reward $R=1$, while the punishment for both defectors is $P=0$. When a C meets a D , the former obtains the sucker's payoff $S=0$, and the latter gets the temptation to defect $T=b \in [1, 2]$ [9].

We consider explicit interaction and strategy-selection time scales for the individuals, and assume the latter is slower than the former. (That is to say, each individual may have played several rounds of game before update her strategy.) This is realized by implementing probabilistic strategy-updating for the individuals: each focal individual i updates her strategy with probability p_i , whose magnitude therefore characterizes her strategy-selection time scale. More specifically, if i does not update her strategy in the present round, in the next round her age will increase by 1; otherwise, i will begin a new lifetime of its strategy and t will restart from 0. In order to evaluate the performance of a strategy during its lifetime, we define a weighted score at time $t \geq 1$ according to the payoffs during the lifetime,

$$G_i(t) = (1-a)G_i(t-1) + ag_i(t), \quad (1)$$

where $G_i(t)$ is contributed by two parts: one is her current payoff $g_i(t)$ weighted by parameter a and the other is her previous gain $G_i(t-1)$ weighted by $1-a$. This definition is inspired by *maternal effect* [49]. The magnitude of a characterizes the weight of current payoff at t in assessing the score of a strategy. If $a=1$, the strategy is evaluated absolutely by the latest gain while decreasing a enhances the weight of earlier payoffs. The weighting scheme takes into account both the memory effect and the inclination of individuals in weighing their current and past benefits to provide a reasonable evaluation for a strategy instead of according to the oversimple average payoff over the lifetime of a strategy. Based on the weighted score, individuals update their strategies by comparing their scores with randomly selected neighbors. In particular, an arbitrary individual i updates its strategy by following a randomly select neighbor j with probability:

$$W_{j \rightarrow i} = \frac{1}{1 + \exp[(G_i - G_j)/\kappa]}, \quad (2)$$

where κ characterizes the noise, and for simplicity it is set to 0.01 [50]. Otherwise, with probability $(1 - W_{j \rightarrow i})$ the focal individual i preserves her own strategy. No matter whose strategy is succeed to impose on i , we reset the age of the new strategy to zero, and the relevant initial score to $G_i(0) = 0$.

An arbitrary individual i is allowed to adjust adaptively her time scale p_i when she competes with an opponent holding different strategy after the strategy updating process: if i wins the competition with j (with probability $1 - W_{j \rightarrow i}$), her strategy-selection time scale will decrease to $p_i = p_i - \beta$; whereas if i accepts j 's strategy, she will increase her time

scale to $p_i = p_i + \alpha$. This evolutionary rule for strategy-selection time scale can be termed as "win-slower, lose-faster," and the pair of (α, β) characterizes the speed that individuals alter their time scales. The larger the value $\alpha(\beta)$ is, the faster the losers (winners) decrease (increase) the lifetime of their current strategies so that the average lifetime of the individuals is inversely correlated with their strategy-selection time scale. The physical content of our model can be understood in the social perspective. If an individual is satisfied with the profits gained by the current strategy, she will naturally tend to hold the strategy for relatively longer time before the next evaluation; otherwise, if the current strategy cannot bring sufficient payoff, an individual will be prone to learn from others and change the current strategy fast. This adaptive scenario is naturally captured by the strategy-selection time scale in our model in which the degree of satisfaction for a strategy is characterized by its weighted score Eq. (1) graded during its lifetime. As a remark, since the performance of a strategy can be only reflected by the payoffs during its lifetime, once a new strategy is employed, its initial score $G(0)$ is set to zero and the benefit obtained by former strategies is not inherited.

The effect of parameter a on the game dynamics has been addressed in [48]. In our present study, we simply set it as 0.1 and focus our attention on the effect of adaptive strategy-selection time scale on the evolution of cooperation. By simulation, each individual selects C or D with equal probability and has the same time scale $p_i = 1.0$ in the initial time. Since too low selection time scale will frozen individuals' evolution, we restrict the lower bound of p_i to $p_{\min} = 0.1$, and the upper bound to $p_{\max} = 1.0$. Herein, the loser (winner) increases (decreases) her time scale by $p_i = \min(p_i + \alpha, p_{\max})$ [$p_i = \max(p_i - \beta, p_{\min})$], and the parameters α and β are constrained to the region $[0.0, 0.9]$. One Monte Carlo step is counted when all individuals have been considered on average once for possible reproduction. The frequency of cooperators f_C are obtained within 10^4 steps after a transient time of 4×10^4 steps, and the data presented below are obtained by averaging over 20 independent trials.

III. RESULTS AND ANALYSIS

It has been reported that increasing b can result in the extinction of cooperators [10,15,20,33,51]. In light of this point, we first study the extinction threshold of C , or the emergence of all D , b_D by tuning α and β in the region $[0.0, 0.9]$. Figure 1 shows that b_D increases monotonously with the increase of α , indicating that the rapid addition of loser's strategy-selection time scale can favor cooperation. We also note that the best situation for cooperation occurs at the region where $\beta \approx 0.1$ and $\alpha \approx 0.9$ (where b_D can go up to 1.40), and too large or too small β does not benefit cooperative behavior [52]. Below we analyze the effects of α and β on the evolution of f_C , respectively.

Let us first consider the situation that the individuals can only decrease their p . This is done by setting $\alpha = 0.0$ and studying f_C as a function of b for several values of β . The simulation results are presented in Fig. 2(a). For $(\alpha, \beta) = (0.0, 0.0)$, which means that each individual updates strat-

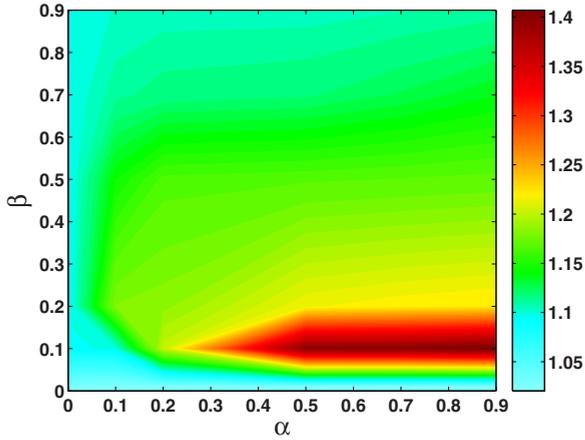


FIG. 1. (Color online) The extinction threshold of cooperators, or the emergence of all defectors, b_D in dependence on the parameters α and β varying from 0.0 to 0.9.

egy immediately after one round of game, the cooperative behavior disappears at $b \approx 1.02$. With the increase of β , we observe f_C is remarkably increased, and b_D goes up to 1.09 for large β . In the inset of Fig. 2(a) we plot the average strategy-selection time scale of the individuals at the steady state, $\langle p \rangle$, as a function of b . For $\alpha=0$ and $\beta>0$, the individuals will decrease their time scales until the lowest bound, $p_{\min}=0.1$. Therefore, f_C for the case of $\beta=0.1$ is coincided with the case where all individuals have $p=0.1$. However, we note that if β is sufficiently small, e.g., $\beta=0.01$, the long trip of $\langle p \rangle$ to p_{\min} is hindered by high temptation to defect.

To get a visualized view, we plot the time series of f_C , and the average strategy-selection time scale difference between C and D , $\langle p_C \rangle - \langle p_D \rangle$, in Fig. 2(b) for $b=1.03$. In Figs. 2(c) and 2(d) we also show, respectively, the typical snapshots of individuals with different strategy-selection time scales at the transient and steady states. Here the color coding is as follows: yellow/light gray (blue/black) represents C (D) whose strategy-selection time scale is less than 0.5, and green/gray (red/dark gray) denotes C (D) larger than 0.5, respectively.

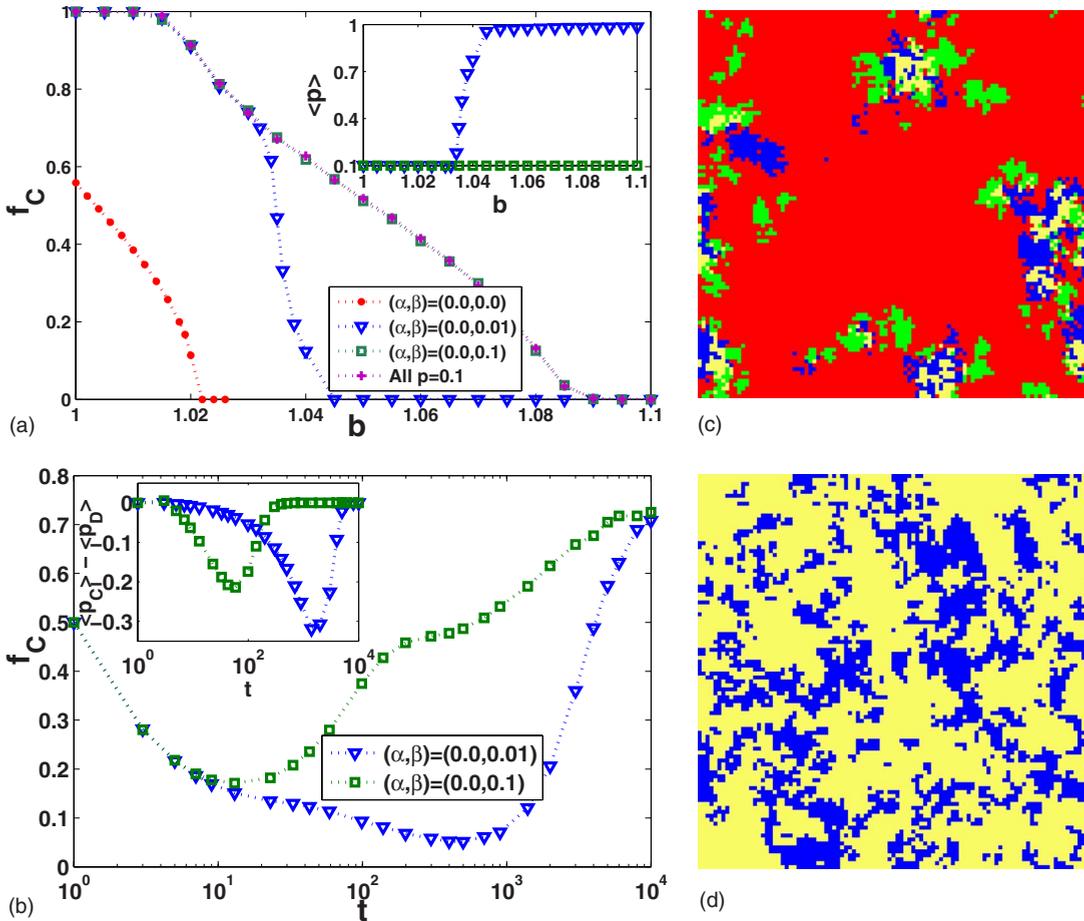


FIG. 2. (Color online) (a) The average frequency f_C of cooperation as a function of the temptation to defect b for $\alpha=0.0$ and $\beta=0.0, 0.01, 0.1$ (from the bottom to the top, respectively). The cross represents the case that all individuals have the same fixed strategy-selection time scale 0.1. The inset: the average time scale $\langle p \rangle$ of the individuals versus b for $\beta=0.01, 0.1$. (b) Time series of f_C and the strategy-selection time scale difference between C and D , $\langle p_C \rangle - \langle p_D \rangle$ (inset) for $\beta=0.01, 0.1$, and $b=1.03$. (c) and (d) illustrate the distribution of the individuals with different time scales at the transient state (1000th MC step) and the steady state (50000th MC step) for the case of $(\alpha, \beta)=(0.0, 0.01)$ and $b=1.03$. In (c) the percent of C with low (high) time scales is 4.2% (9.0%), which is represented by yellow/light gray (green/gray) color. There are 7.2% (79.6%) of D with low (high) time scales who are denoted by blue/black (red/dark gray) color. In (d) there are 69.7% of cooperators (yellow/light gray) and others are defectors (blue/black) who have the same time scale with 0.1.

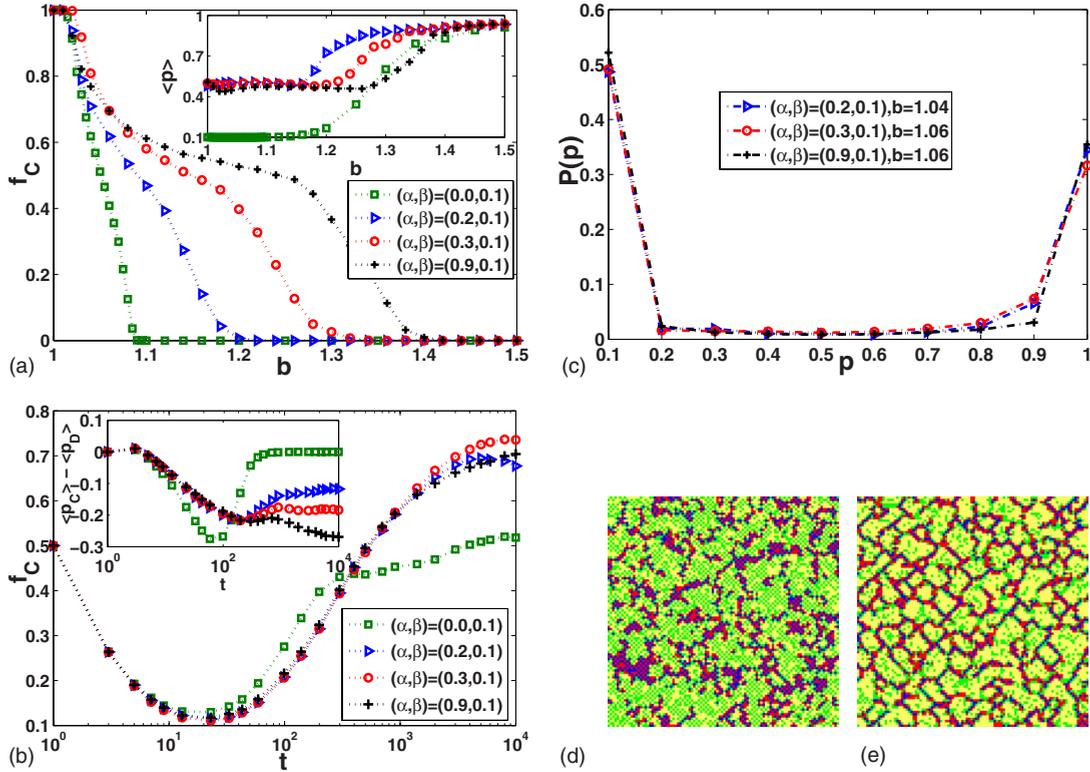


FIG. 3. (Color online) f_C and $\langle p \rangle$ (inset) versus b for $\beta=0.1$, and α varying from 0.0 to 0.9. (b) The time series of f_C and $\langle p_C \rangle - \langle p_D \rangle$ (inset) are plotted when the individuals face the same temptation $b=1.05$ for different values of α . (c) The time scale distribution of the individuals at the steady state where appropriate $b=1.04, 1.06, 1.06$ are selected so that there are similar cooperation levels ($f_C = 0.718, 0.703, 0.694$) for $\alpha=0.2, 0.3, 0.9$, respectively. (d) and (e) are snapshots at the 50 000th MC step for $b=1.04$ and $(\alpha, \beta) = (0.2, 0.1)$, and $b=1.06$ and $(\alpha, \beta) = (0.9, 0.1)$. In the former (latter) case the percents of cooperators with low and high time scales and the defectors with low and high time scales are 40.2% (47.4%), 30.1% (22.3%), 13.6% (10.6%), and 16.1% (19.7%), which are denoted by yellow/light gray, green/gray, blue/black and red/dark gray colors, respectively.

We observe from Fig. 2(b) that with time goes on, $\langle p_C \rangle - \langle p_D \rangle$ first reduces to negative value, and then ascends to zero in the steady state. The reason is that at the beginning D can obtain temporary high payoff and attract more followers. As a result, the D -cluster will grow rapidly, and most defectors would own high selection-strategy time scales [Fig. 2(c)]. On the other hand, the cooperators form compact clusters to defend the invasion of defection [14]. Occasionally, some successful cooperators would possess low $\langle p \rangle$, which would reciprocate them further. This leads to the increase of f_C after some transient time [Fig. 2(b)]. We note that smaller value of β , say 0.01 will give rise to longer time for f_C to touch the “bottom.” This is reasonable, since sufficiently small β does harm to the long time reciprocity between cooperators, and hence favors the diffusion of defection [Fig. 2(a)]. Consequently, the cooperation is easy to disappear in the case of sufficiently small β . This is also the reason that b_D for $\beta=0.01$ is smaller than that for $\beta=0.1$ in Fig. 2(a).

Furthermore, we like to compare the effect of the decrease of individuals’ strategy-selection time scale with the increase of the teaching ability studied in [32,34]. It is noteworthy that the individual with high teaching ability (or called leader) can effectively make its neighbors following its strategy. This leads to the higher leaders’ influences that furthermore prevent the change of its neighbors’ teaching ability. Therefore, at the steady state the influence distribution is

heterogeneous, i.e., there are only a few leaders who are surrounded by lots of individuals with lower influence [34]. In contrast, in the present study the individuals with lower time scales can only hold on their current strategies for longer time but this behavior cannot actively change their neighbors’ behaviors. Therefore, individuals can freely decrease their time scales to resist the invasion of neighbors, which allows defectors or cooperators with low time scales gathering together and leads to the uniform time scale under the case of $\alpha=0$ [Fig. 2(d)].

We now fix $\beta=0.1$ and tune α to study how α influences the evolution of cooperative behavior. The simulation results are summarized in Fig. 3. For $(\alpha, \beta) = (0.0, 0.1)$, the cooperators disappear at $b_D \approx 1.09$. For $\alpha > 0$, we notice that the average time scale $\langle p \rangle$ raises and the cooperation is enhanced, which is reflected not only by large f_C for the same value of b , but also by the increase of b_D which can even reach 1.40. As before, in Fig. 3(b) we plot the time series of f_C and $\langle p_C \rangle - \langle p_D \rangle$ (inset) for a typical value of $b=1.05$. For $(\alpha, \beta) = (0.0, 0.1)$ the individuals can only decrease their strategy-selection time scale, $\langle p_C \rangle - \langle p_D \rangle$ vanishes at the steady state. For the cases of $\alpha > 0$, the value of $\langle p_C \rangle - \langle p_D \rangle$ can maintain negative at the steady state, which indicates that the cooperators are on average more successful than defectors (since the strategy-selection time scale of losers will be raised).

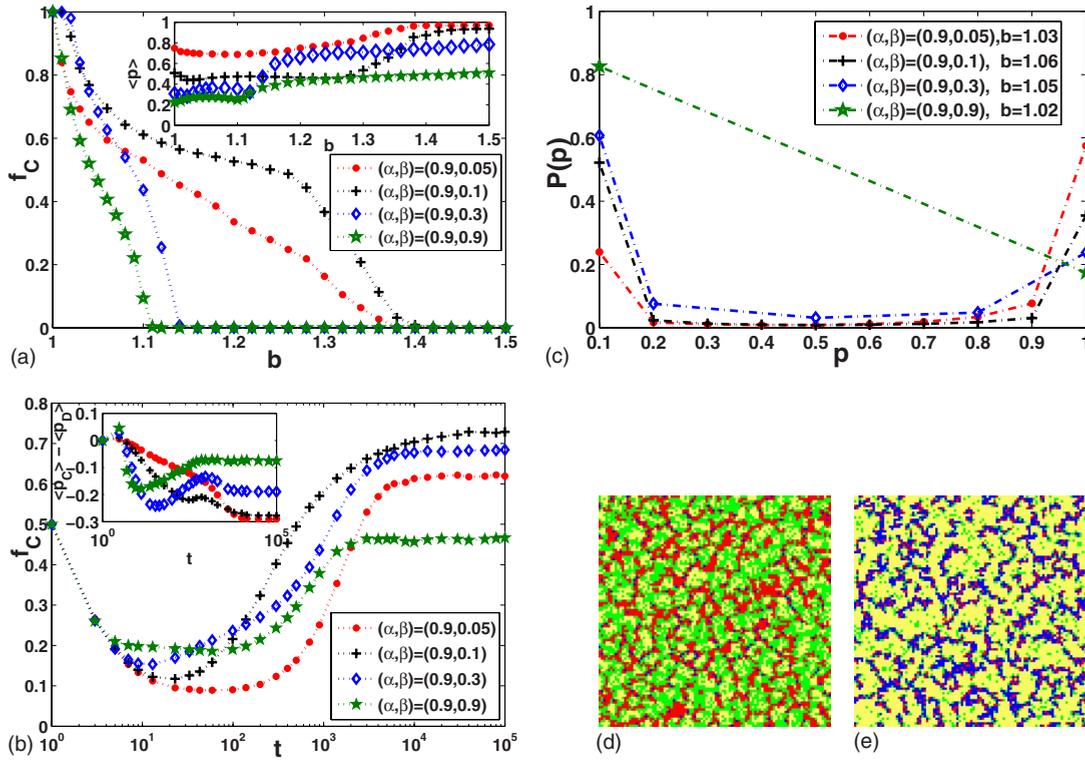


FIG. 4. (Color online) (a) f_C and $\langle p \rangle$ (inset) as the function of b for $\alpha=0.9$ and β varying from 0.05 to 0.9. (b) The time series of f_C and $\langle p_C \rangle - \langle p_D \rangle$ (inset) for $b=1.05$ and different values of β . (c) The time scale distribution of the individuals at the steady state are plotted for $b=1.03, 1.06, 1.05, 1.02$, and $\alpha=0.05, 0.1, 0.3, 0.9$. The final f_C is 0.696, 0.694, 0.687, 0.691, respectively. Typical snapshots of strategies of the individuals at the 500 00th MC step for $(\alpha, \beta)=(0.9, 0.05)$ and $(0.9, 0.9)$ are plotted in (d) and (e), where b is set to 1.03 and 1.02, respectively. The percent of C (D) with low and high time scale are 26.1% and 42.6% (2.5% and 28.8%) for the former case, and 60.3% and 10.2% (21.4% and 8.1%) for the latter case.

We further investigate the strategy-selection time scale distribution of the individuals at the steady state, $P(p)$, for different values of α . To do so, we select appropriately the value of b to obtain similar $f_C \approx 0.7$ in the final state. The results are shown in Fig. 3(c) where we observe similar U shape distribution of $P(p)$ for different α . This indicates that the strategy-selection time scale of the individuals tend to reach the two boundary value $p_{\min}=0.1$ and $p_{\max}=1.0$. Though this result is somewhat expected, it is interesting to point out the similarity of this observation with that in the evolutionary minority game: the individuals can self-segregate into two extreme behaviors to obtain optimal benefit, leading to U shape distribution as well [53]. We expect that the U shape distribution of individuals' strategies might be an instructive index in finding optimal solution for multi-agent collective behavior.

Figures 3(d) and 3(e) show the typical snapshots of the strategy-selection time scales of the individuals for $\alpha=0.2$ and 0.9, respectively. Comparing the two snapshots with similar cooperation level, we notice that as α increases, C with low time scales tend to compose large compact clusters, and D with low time scales is decreased. This observation can be understood as follows. Successful individuals (high score) will attract their neighbors to imitate their behavior. The imitation will however produce totally different feedback to C and D . Successful C will have more cooperative neighbors that enhance their payoffs reciprocally. But for D ,

the imitation of neighbors results in a negative feedback that weakens the focal D 's payoff. Since successful C can form stable cluster (due to the long-term reciprocity), for larger α , their losing D neighbors (if any) could learn their behavior more frequently and have greater chance to becoming C , hence cooperation is promoted.

We now turn to investigate the impact of β on the evolution of cooperation. We first study f_C as a function of b for several values of β by fixing $\alpha=0.9$. We present our simulation results in Fig. 4(a), where for too small $\beta=0.05$ or too large $\beta=0.9$, the cooperative behavior is hard to persist in the system. It is interesting that the highest level of cooperation emerges at $\beta \approx 0.1$, where the cooperators can persist in the system even b is greater than 1.40. The nonmonotonic behavior of f_C with β can be understood as follows. In the case of $\beta \rightarrow 0$, the winners reduce their time scale slowly and the cooperators have negligible chance to form long term reciprocal clusters. Therefore, there are long relaxation time as well as low cooperation level at the transient state [Fig. 4(b)], and high $\langle p \rangle$ at the steady state [inset of Fig. 4(a)]. While for too large β , the defectors can reduce their time scale severely and they can exploit their C neighbors to get considerably high payoff. Therefore, there are small time scale difference between C and D [inset of Fig. 4(b)] which would benefit the diffusion of defection. Combining the effects of the two factors, it can be expected that there exists an appropriate β for the population to achieve highest level of cooperation.

The distribution of the strategy-selection time scales of the individuals in the steady state are shown in Figs. 4(c)–4(e), where we select proper b to achieve similar final cooperation levels. From Fig. 4(c) we can find that as β increases, there are more individuals locating at $p=0.1$ and less at $p=1.0$. Comparing Figs. 4(d) and 4(e), we notice clearly that for small $\beta=0.05$, the individuals tend to hold large values of p and the cooperators fail to compose long-term reciprocal clusters. For the large value of $\beta=0.9$, there are more defectors with low time scale that enhances the persistence of defection. These results corroborate our previous analysis.

IV. CONCLUSION AND DISCUSSIONS

In this paper we have studied the coevolution of individuals' strategy-selection time scale and their strategies in the context of evolutionary spatial prisoner's dilemma game. Individuals can adaptively adjust their strategy-updating frequency in term of the win-slower, lose-faster rule. The adjusting speed of strategy-selection time scale is controlled by two parameters, α and β . By studying the average frequency of cooperation, the strategy-selection time scale distribution, and the pattern formation of individuals in the steady state, we have found that the faster the losers increase their strategy updating frequency, the easier the cooperators can form long-term clusters which sustain cooperation. On the other hand, decreasing strategy-selection time scale extremely slowly or fast will hinder the emergence of cooperation. This is because in the former case the time for the cooperators is not sufficient to establish long-term reciprocity, while in the latter case the defectors can efficiently exploit cooperators due to their long lifetime. Consequently, proper value of β benefits the formation of long-term cooperative clusters and inhibit defection. The cooperation is thus facilitated by the rule win-slower, lose-faster.

We have also examined our conclusion by implementing the alternative multiplicative strategy-selection time scale for the selection time scale, i.e., the individual i will decrease her time scale by $p_i=p_i/\beta$ if she resists the invasion of an opponent, otherwise increases by $p_i=p_i\alpha$. The alternative evolving rule of strategy-selection time scale yields qualitatively similar results.

Finally, we would like to discuss the relation between our work and that of Ref. [47]. Roca *et al.* investigated a well-mixed population where the individuals hold fixed time scales for both selection and interaction. It has been found that if the time scale of selection is slower than that of interaction, the cooperators have adequate chance to interact with other cooperators, such that they can gain (on average) higher payoffs than defectors, hence cooperation is facilitated. In our model, the spatial population is considered and some clusters of individuals holding the same strategy might emerge. As has been known, cooperators can survive by forming compact clusters. Along the boundary of cooperator cluster, the average payoff of cooperators are on average greater than those of the defectors [54]. When these cooperators compete with their defective neighbors, they can highly probability win. As a result, the strategy-selection time scale of these cooperators will decrease, which in turn reinforce further the stability of the cooperator-cluster. In addition, the boundary defectors lose with greater probability when competing with their cooperative neighbors. Consequently, their strategy-selection time scale will increase and they will learn frequently from their neighbors, which would benefit the growth of cooperator-cluster. Moreover, the win-slower, lose-faster rule also stably increases the payoffs of cooperators. In this regard, our model is essentially consistent with the work of Ref. [47]. We believe that our work can yield some insight into the design of consensus protocol in multi-agent systems [55], i.e., through selecting proper rules to turn the lifetime of selfish individuals' strategies, the expectant collective behaviors could emerge and the social optimum might obtain.

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