

**Role of adaptive migration in promoting cooperation in spatial games**Luo-Luo Jiang,<sup>1</sup> Wen-Xu Wang,<sup>2</sup> Ying-Cheng Lai,<sup>2,3</sup> and Bing-Hong Wang<sup>1</sup><sup>1</sup>*Department of Modern Physics, University of Science and Technology of China, Hefei 230026, China*<sup>2</sup>*Department of Electrical Engineering, Arizona State University, Tempe, Arizona 85287, USA*<sup>3</sup>*Department of Physics, Arizona State University, Tempe, Arizona 85287, USA*

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Recent work has revealed that success-driven migration can promote cooperation among selfish individuals in evolutionary games. This migration mechanism relies, however, on nonlocal information about the states of the individuals and their computational capabilities for prediction. We investigate the role of adaptive migration in cooperative behavior in the framework of spatial game by proposing an alternative migration strategy that requires only *local information* obtainable through game interactions. Our results demonstrate that adaptive migration can be effective in promoting cooperation in two ways. First, there exists an optimal degree of migration associated with the density of empty sites and migration speed, which leads to the highest level of cooperation. Second, adaptive migration can induce an outbreak of cooperation from an environment dominated by defectors. These findings hold for common types of evolutionary games that involve pairwise interactions.

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**I. INTRODUCTION**

Cooperation is a fundamental phenomenon in a variety of biological, social, and economical systems that involve a large number of interacting individuals [1–5]. The emergence of cooperation among selfish individuals has been an interesting problem, partly due to the well-known social dilemma that disfavors cooperation. Evolutionary games have been an effective framework to address the conflict between the interests of selfish individuals and cooperation [6–9]. Two types of games that are commonly used in this context are the prisoners' dilemma game (PDG) and the snowdrift game (SG) [10]. For both types of games, when all the individuals cooperate, a steady state can arise where the collective interest of all individuals is realized. But for a well mixed ensemble of individuals, defection can always bring in temporarily high payoffs, so individuals tend to take on this strategy. When a sufficient number of individuals choose to defect, the state of cooperation becomes unstable. This would suggest that cooperation cannot be expected in complex systems, the essence of the aforementioned social dilemma. To explore fundamental mechanisms for cooperation has thus become an interdisciplinary topic of broad interest. So far, a number of mechanisms have been explored, including repeated interactions [1], spatial extensions [11], reciprocity [12], strategic complexity [13], adaptive network [14], memory effects [15], partially random contacts [16], teaching activity [17], and social diversity [18].

Quite recently, a new mechanism for stabilizing and sustaining cooperation has been discovered, which is based on the idea of success-driven migration in evolutionary games occurring on spatially extended environments [19]. The basic hypothesis in [19] is that individuals tend to migrate to available spatial sites that can potentially bring in better payoff. This can be regarded as an adaptive migration, in contrast to random movement [20,21]. In particular, an individual explores the possible payoffs for empty sites, and move to the empty site in a neighborhood area with the highest expected

payoff provided that it is higher than the current payoffs of the individual. This behavior can be regarded as “fictitious play.” As a result, cooperators are driven to form clusters that are stable and resilient to the invasion of defectors, and cooperation can be considerably enhanced, compared to the situation of random migration [21]. The main finding in Ref. [19] is that, when such migration is allowed in a noisy environment, cooperation can emerge even in spatial regions that are surrounded by defectors. This is quite significant, considering that migration is a central feature in real ecosystems and in human societies.

To realize the “fictitious play,” nonlocal information is required, such as the states of players around empty sites which, however, may not be available. For example, if an individual wants to identify better neighboring sites to migrate into, information about the players in the neighborhoods of these sites is needed, which usually cannot be obtained directly through game interactions. To obtain such information in real times, additional channel beyond the framework of evolutionary game theory and intensive computations may be required. At the present, the interplay between adaptive migration and cooperation in spatial games is far from being well understood, a situation different from games on adaptive networks, a relatively well-developed area [14].

A basic question is then whether cooperation can be facilitated by adaptive migration when only local information is available to any individual. The purpose of this paper is to address this issue by proposing an adaptive migration strategy with the restrictions of local-information availability and limited computational power. Under these constraints, individuals can perform an adaptive movement in order to gain higher payoffs or enhance their fitness. Based on local information, individuals can evaluate the advantages and disadvantages of their current sites by simply counting the number of neighboring cooperators and defectors. Note that individuals can always gain more payoffs from playing with cooperators than selfish defectors, regardless of their own strategies. The desire of playing with cooperators instead of

defectors can be a driving force of population mobility, besides success-driven migration [19]. For example, if an individual is in an environment surrounded by defectors, the individual tends to move to possibly gain higher benefit. In contrast, if an individual's neighbors are cooperators, the individual would prefer not to migrate. In ecosystems, the number of neighboring defectors can be a way to measure the "risk" of a site and species have the natural tendency to evade dangerous places or situations. This critical piece of information can, however, be obtained through gaming interactions with neighboring individuals of the target site. This migration strategy thus distinguishes our work from that in Ref. [19]. The migration probability can then be assumed to be governed by the relative numbers of defecting and cooperating neighbors. We shall use both PDG and SG and focus on the effect of population density on cooperation. Our findings are that adaptive migration can generally lead to highest level and outbreak of cooperation. We develop a phenomenological understanding by examining the organization of spatial patterns emerging from the dynamics of evolutionary games.

In Sec. II, we introduce a model to incorporate adaptive migration in spatial games. In Sec. III, we present results of optimal cooperation based on the density of empty sites and spatial patterns. In Sec. IV, we demonstrate the occurrence of outbreak of cooperation in our model. In Sec. V, we discuss the effect of migration speed on cooperation. We finally conclude the work in Sec. VI.

## II. SPATIAL GAMES WITH ADAPTIVE MIGRATION

For a typical two-player evolutionary game (PDG or SG) on a spatial domain, individuals occupy sites of a square lattice. Each individual can choose to cooperate (C) or defect (D), and the evolutionary dynamics is described by the following payoff matrix:

$$\begin{array}{cc} & \begin{array}{c} \text{C} \\ \text{D} \end{array} \\ \begin{array}{c} \text{C} \\ \text{D} \end{array} & \begin{pmatrix} R & S \\ T & P \end{pmatrix}, \end{array} \quad (1)$$

where the matrix elements represent the payoffs for the players in the row,  $R$  is the reward for mutual cooperation,  $P$  is the punishment for mutual defection,  $T$  is the temptation to defect, and  $S$  is the sucker's payoff. A PDG differs from a SG in the ordering of payoff values. In particular, for PDG, the payoff ranking is  $T > R > P > S$  and it is  $T > R > S > P$  for SG. For concreteness, equivalent rescaled payoff matrices for the two types of games can be used [11]: for PDG, we have  $R=1$ ,  $S=0$ ,  $T=b$ , and  $P=0$ ; for SG, we have  $R=1$ ,  $S=1-r$ ,  $T=1+r$ , and  $P=0$ . Each game is thus controlled by a single parameter:  $b$  for PDG ( $1 < b < 2$ ) and  $r$  for SG ( $0 < r < 1$ ).

We start the evolutionary game by placing  $N$  individuals on a square lattice of  $L \times L$  sites with periodic boundary conditions. Each site can be either empty or occupied by one individual. Empty sites represent spatial regions that individuals can migrate into. In our simulations, the fraction of empty sites is  $d_0$ . The population density is given by  $1-d_0$ .

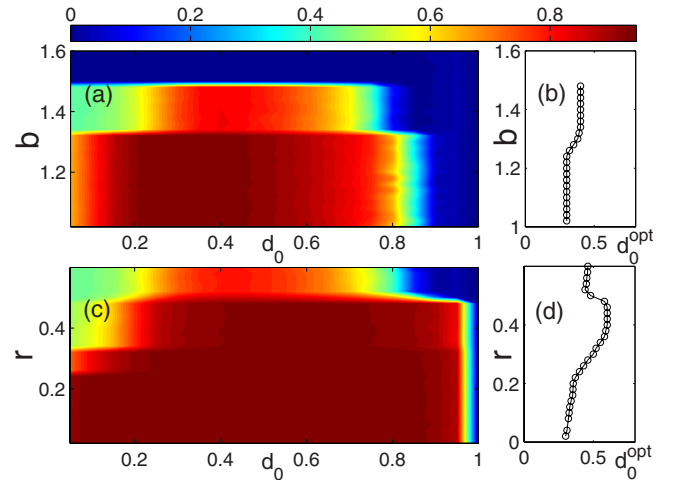


FIG. 1. (Color online) Color-coded values of  $\rho_C$  for (a) PDG in the  $(d_0, b)$  parameter space and for (c) SG in  $(d_0, r)$  space. The color scale is linear. Panels (b) and (d) show the optimal value of  $d_0$  associated with the maximum value  $\rho_C$  as a function of  $b$  for PDG, and of  $r$  for SG, respectively. The lattice size is  $50 \times 50$ . The quantity  $\rho_C$  is obtained by averaging over 1000 time steps after 9000 time steps for one realization and each data point is averaged over 1000 different realizations. We have examined that after 9000 time steps, the value of  $\rho_C$  is stabilized.

Individuals are updated asynchronously in a random sequential order by two processes at each time step: migration and strategy updating. During the migration, we randomly select an individual. To decide the site to move into, the chosen individual counts the number of defectors in its own neighborhood,  $n_D$ . After that, the individual moves to an empty site with the probability  $n_D/4$ . If there are more than one empty site, one is selected randomly. If all neighboring sites are empty, one is selected randomly for the individual to migrate into. After the migration, with probability  $1-\gamma$ , the individual updates its strategy by comparing its payoff with its neighbors' payoffs resulted from all game interactions. The individual is allowed to imitate the strategy with the highest score among the individual itself and its immediate neighbors [11]. With probability  $\gamma$  ( $\gamma \ll 1$ ), the individual randomly reset its strategy. Here  $\gamma$  characterizes the effect of environmental noise or uncertainty in decision making.

## III. COOPERATION INDUCED BY MIGRATION

In our simulations, initially nonempty sites are occupied by defectors or cooperators randomly, and  $\rho_C$  is the ratio of the number of cooperators over the total number of individuals. Our computations reveal that the density of empty sites, or equivalently, the population density in the system, can affect the emergence of cooperation for both PDG and SG. For  $d_0=0$ , there is no migration. As  $d_0$  is increased from zero,  $\rho_C$  can increase. The dependence of the cooperation level on both  $d_0$  and the temptation-to-defection parameter is shown in Figs. 1(a) and 1(c) for PDG and SG, respectively. We find that the  $\rho_C$  can be maximized when  $d_0$  reaches some optimal value, as shown in Fig. 1(b) for PDG and Fig. 1(d) for SG.

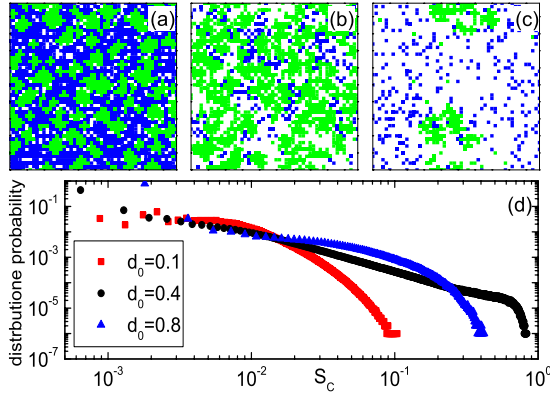


FIG. 2. (Color online) For  $b=1.4$  in PDG, typical snapshots of spatial patterns of cooperators and defectors on a  $50 \times 50$  square lattice obtained for different value of  $d_0$ . The color coding is as follows: green (light gray) represents a cooperator; blue (dark gray) represents a defector; white represents an empty site. Panels (a)–(c) correspond to  $d_0=0.1$ ,  $d_0=0.4$ , and  $d_0=0.8$ , respectively. Panel (d) displays the probability distribution of  $S_C$ , the normalized sizes of various cooperator clusters. The distribution of  $S_C$  is obtained from 5000 time steps after 10 000 time steps for one realization, and 1000 different realizations are carried out.

We note that for low densities of empty sites, our adaptive migration strategy based on local information can lead to a high cooperation level, which is similar to the results from the migration strategy based on nonlocal information as proposed by Herbing and Yu [19]. For high densities of empty sites, e.g.,  $d_0 > 0.8$ , the migration strategy based on nonlocal information can lead to stronger cooperation than our adaptive migration. This is due to the fact that the availability of nonlocal information favors communication among sparsely dispersed individuals, so the aggregation of individuals and the formation of cooperator clusters become more likely in the presence of nonlocal-information based migration. While requiring no cost of acquiring nonlocal information, our migration strategy cannot induce the formation of cooperator cluster for very low population densities. Since cooperator clusters are key to sustaining cooperation, the nonlocal-information based migration strategy tends to better promote cooperation for low population densities.

An analytic understanding of the phenomenon of optimal cooperation induced by adaptive migration appears difficult at this time. We thus seek to explain the phenomenon qualitatively, with the aid of numerical simulations. For example, we have examined the spatial patterns after the system reaches a steady state, as shown in Fig. 2. For low values of  $d_0$  [e.g., Fig. 2(a)], the patterns are similar to those in the original spatial game in the absence of migration where cooperators form small clusters to resist the invasion of defectors [22]. Some empty sites are interspersed in the spatial structure. For large values of  $d_0$  [e.g., Fig. 2(c)], cooperators aggregate into a few clusters while defectors disperse in the ocean of vacant sites. Because of the availability of space for migration, the boundary of cooperator clusters can be transformed under the aggression of defectors. For the optimal value  $d_0=0.4$  [Fig. 2(b)], cooperators are interconnected and form one large cluster that nearly fills the entire spatial do-

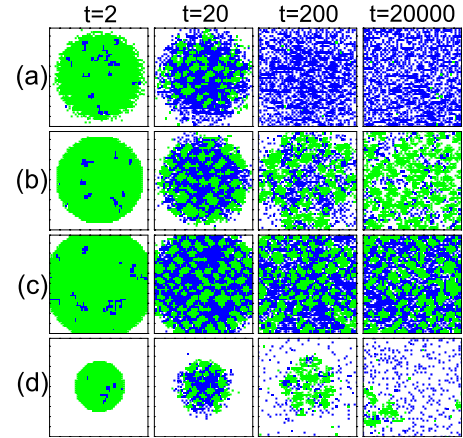


FIG. 3. (Color online) Evolution of spatial patterns for different values of vacation density  $d_0$  for PDG on a  $50 \times 50$  square lattice. The color coding is as follows: green (light gray) represents a cooperator; blue (dark gray) represents a defector; and white represents an empty site. The four panels in (a) are snapshots of different time steps for  $d_0=0.4$  with random migration. With adaptive migration, snapshots of patterns at different time are shown in (b)–(d) for  $d_0=0.4$  (approximately the optimal value),  $d_0=0.1$ , and  $d_0=0.8$ , respectively.

main. Defectors can hardly survive in the interspatial sites among cooperators. We have also calculated the distribution of normalized cluster sizes for different values of  $d_0$ , which is defined as  $S_C = N_C / N_p$ , where  $N_C$  is the number of cooperators in a cluster and  $N_p$  is the number of individuals in the system. Figure 2(d) shows the probability distribution of  $S_C$ . We see that for  $d_0=0.4$ , there is an appreciable probability for large clusters of cooperators to emerge. This indicates that an appropriate population density can facilitate the formation of large cooperator clusters. Theoretically, how adaptive migration promotes the formation of cooperator clusters is an open question.

A related question is whether the migration mechanism is effective to resist erosion of cooperator clusters by a small number of defectors embedded within. To address this, we study the evolution of spatial patterns for situations where a small number of defectors are initially embedded in a large cluster of cooperators. To assess the effectiveness of adaptive migration, we shall compare with the case of random migration, as shown in Fig. 3(a). We observe that defectors can erode cooperators from inside and randomly moving cooperators fail to form compact clusters. Only a few filamentlike clusters are aggregated. Ultimately, defectors dominate the population. In contrast, for adaptive migration, as shown in Fig. 3(b) for  $d_0=0.4$ , the number of defectors increases only at the early stage of evolution, while cooperators tend to move away from the defectors. After the rising of some compact cooperation clusters, defectors are overwhelmed by cooperators. Due to the appearance of empty sites between cooperators and defectors as a result of migration, defectors cannot gain enough profits from neighbors and thus become vulnerable to nearby cooperators. As a result, cooperators tend to dominate eventually. Comparing Fig. 3(a) with Fig. 3(b), we see that adaptive migration can be effective for forming cooperator clusters, but random migration tends to favor defection.

Figures 3(c) and 3(d) provide an explanation as to why the density of vacant sites can affect the degree of cooperation in a significant way. In particular, in Fig. 3(c), compact cooperator clusters are formed associated with the increase of defectors. However, due to the limited number of empty sites, cooperators inside the large cluster can hardly move so that no empty sites can arise between cooperators and defectors. Despite the ability for cooperator clusters to resist the invasion of defectors, they can exploit nearby cooperators to gain much payoff and thus are not outperformed by cooperators. This restriction in migration precludes the aggregation of large cooperator clusters to sustain cooperation. On the other hand, when there is a large number of empty sites, as shown in Fig. 3(d), cooperators have many choices for migration so that their chances to meet and form compact clusters during the migration are small. Cooperators are erode by nearby defectors gradually and become extinct ultimately. Defection is favored again when the density of vacant sites is large.

For random migration and adaptive migration with high density of empty sites, the cooperation density  $\rho_c$  can be understood through a mean-field analysis. In both cases, individuals can be assumed to be well mixed and the evolution of  $\rho_c$  can be expressed as

$$\frac{\partial \rho_c}{\partial t} = \rho_c(1 - \rho_c - d_0)[\text{sgn}(M_C - M_D) - \text{sgn}(M_D - M_C)] + \delta, \quad (2)$$

where  $M_C$  and  $M_D$  denote the payoffs of cooperators and defectors respectively, and  $\text{sgn}$  is a sign function. The mean-field approximation yields  $M_C = 4\rho_c$  and  $M_D = 4b\rho_c$ , we thus have

$$\frac{\partial \rho_c}{\partial t} = -2\rho_c(1 - \rho_c - d_0)\text{sgn}(4\rho_c - 4b\rho_c) + \delta < 0, \quad (3)$$

which indicates that  $\rho_c$  will go to zero for random migration on lattice. This analysis agrees with numerical simulations that for random migration or adaptive migration with high density of empty sites, and  $\rho_c$  tends to assume near-zero values asymptotically.

#### IV. OUTBREAK OF COOPERATION

Our computations reveal the phenomenon of spontaneous outbreak of cooperation induced by local-information based adaptive movement. Similar to Ref. [19], defectors are set to be the exclusive strategy at the beginning. After a period of time that depends on the density of empty sites, cooperation arises abruptly. The phenomenon is exemplified using PDG, as shown in Figs. 4(a)–4(c) for three different values of  $d_0$ . In all three cases, we observe a sudden emergence of a large number of cooperators at some critical time. The formation of cooperator clusters can be effective in resisting invasion of defectors at boundaries and protecting cooperators. The dependence of steady density  $\rho_c$  of the emergent cooperation on  $d_0$  is exhibited in Fig. 4(d). This finding is consistent with that associated with evolution from well mixed population. A quantity that can be used to quantify the degree or the

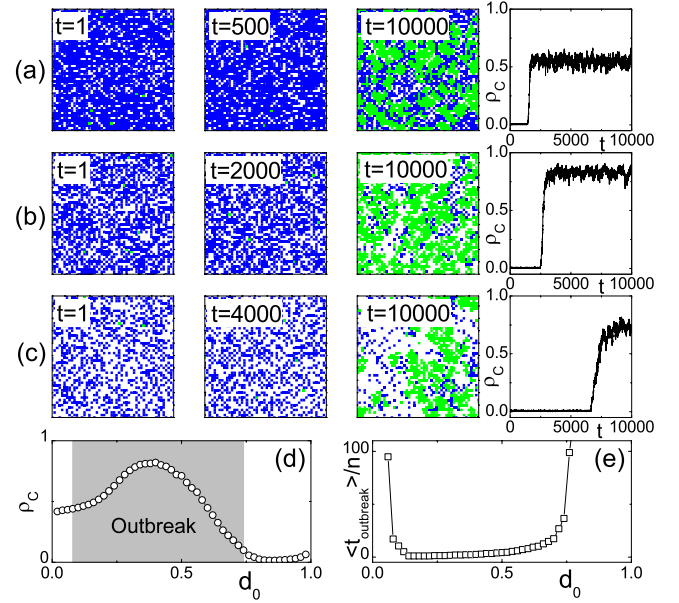


FIG. 4. (Color online) For PDG with parameters  $L=50$  and  $b=1.4$ , evolution of pattern and cooperation fraction with time: for (a)  $d_0=0.1$ , (b)  $d_0=0.4$ , and (c)  $d_0=0.6$ . The color coding is as follows: green (light gray) represents a cooperator; blue (dark gray) represents a defector; and white represents an empty site. Fraction of cooperation and average outbreak waiting time as a function of empty sites' density  $d_0$  are shown in panels (d) and (e), respectively. Results are obtained by averaging over 1000 independent realizations.

strength of outbreak of cooperation is the average transient time  $t_{outbreak}$  before outbreak occurs. Without loss of generality,  $t_{outbreak}$  is defined to be the time for the cooperation density  $\rho_c$  to reach a large value, say 0.5. In a simulation run, if  $\rho_c$  cannot exceed the value,  $\langle t_{outbreak} \rangle$  is set to be  $\infty$ . In Fig. 4(e), the strength of outbreak of cooperation is quantified by  $\langle t_{outbreak} \rangle / n$ , where  $n$  is the number of random realizations in which outbreak occurs, and  $\langle t_{outbreak} \rangle$  is obtained by averaging over all realizations for which outbreak occurs. Thus the lower the value of  $\langle t_{outbreak} \rangle / n$ , the more prevalent outbreak is. The boundary of outbreak region can then be defined by the abrupt transition of  $\langle t_{outbreak} \rangle / n$  in Fig. 4(e). The outbreak region is displayed in Fig. 4(d) in gray. It is noteworthy that outbreak of cooperation can arise even though the average value of  $\rho_c$  is less than 0.5, as shown in Fig. 4(d). This is because the boundary is defined by the sharp transition of  $\langle t_{outbreak} \rangle / n$  and the boundary of outbreak means that the probability of occurrence of outbreak inside the outbreak region close to the boundary is much higher than that outside the outbreak region close to the boundary. These results demonstrate that suitable density  $d_0$  can promote the outbreak of cooperation, and outbreak never occurs for both too small and too large values of  $d_0$ .

To understand the occurrence of outbreak for intermediate values of  $d_0$ , it is useful to analyze two limits,  $d_0=0$  and  $d_0 \rightarrow 1$ . For  $d_0=0$ , individuals cannot move, cooperator clusters can be hardly established, so that  $t_{outbreak}/n \rightarrow \infty$ . In the opposite limiting case ( $d_0 \rightarrow 1$ ), individuals are nearly surrounded by empty sites and movement becomes purely ran-

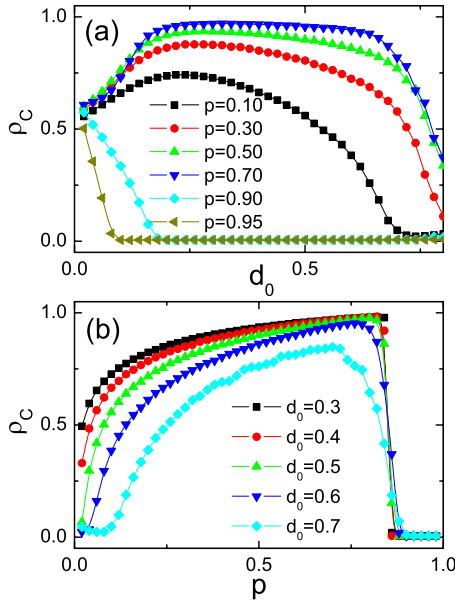


FIG. 5. (Color online) For PDG, (a) fraction of cooperators  $\rho_C$  as a function of the density of empty sites  $d_0$  for different probability  $p$ , and (b) fraction of cooperation  $\rho_C$  as a function of the probability  $p$  for different density of empty sites  $d_0$ . In both cases, the model parameters are  $L=50$  and  $b=1.2$ .

dom, so cooperation is not favored according to the mean-field analysis. Thus, there should be an optimal value  $d_0$  that leads to a maximum degree of cooperation. Our finding reveals that outbreak of cooperation is a robust phenomenon in the presence of adaptive movement, even when the dynamics of game is based on local information only so that the predicted payoff of empty sites is not available [19].

## V. SPEED OF MIGRATION

We have also generalized our model to investigate the effect of migration speed on cooperation by assigning different time scales to both strategy evolution and migration in terms of a parameter  $p$  [21]. At each time step, individuals migrate with probability  $p$ , and play games with probability  $1-p$ . By increasing the values of  $p$ , migration speed is increased. For  $p=0.5$ , the speed of migration is locked to the speed of strategy evolution, recovering the model in Sec. II. We observe that the migration speed  $p$  associated with  $d_0$  has a great influence on cooperation  $\rho_C$ . As shown in Fig. 5(a), for large values of  $p$ , for instance  $p=0.9$  and  $p=0.95$ ,  $\rho_C$  decreases as  $d_0$  increases. For small values of  $p$ ,  $\rho_C$  can be maximized by  $d_0$  for different values of  $p$ . The dependence of  $\rho_C$  on  $p$  for different values of  $d_0$  is shown in Fig. 5(b). We see that suitable value of  $p$  can lead to highest  $\rho_C$  for different values of  $d_0$  as well. These results indicate that an appropriate combination of migration speed and density of empty sites can lead to optimal cooperation.

Another interesting phenomenon observed in Fig. 5(b) is that there exists a sharp transition from domination of cooperation to nearly extinction of cooperators at about  $p=0.85$ . This transition can be understood intuitively by examining the spatial patterns, as displayed in Fig. 6. Without loss of

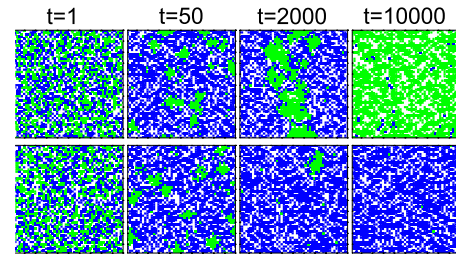


FIG. 6. (Color online) Evolution of pattern with time for  $p=0.84$  (top) and  $p=0.86$  (bottom),  $d_0=0.3$ . The color coding is as follows: green (light gray) represents a cooperator; blue (dark gray) represents a defector; and white represents an empty site. In both cases, the model parameters are  $L=50$  and  $b=1.2$ .

generality, we select two values of  $p$  right before and after the transition, e.g.,  $p=0.84$  and  $p=0.86$ , with fixing  $d_0=0.3$ . In Fig. 6, initially individuals are randomly distributed for both cases. After a short period of time, e.g.,  $t=50$ , due to the effect of adaptive migration, some cooperator clusters are aggregated in both cases. Note that the number and the sizes of the cooperator clusters are similar for both cases. However, after the formation of cooperator clusters, two different evolution paths arise. In particular, for  $p=0.84$ , cooperator clusters gradually expand and eventually occupy the whole lattice, while for  $p=0.86$ , cooperator clusters shrink and finally disappear, and almost no cooperators survive at  $t=10000$ . The factor that causes the distinct evolution paths lies in the attacks from defectors around cooperators after the formation of the cooperator clusters. Cooperators within clusters are relatively immobile but the defectors around them are active and attempt to invade the clusters. The strength of the invasion is determined by the contact frequency of defectors with the clusters, which is determined by the migration speed. As a result, for low migration speed, e.g.,  $p=0.84$ , cooperator clusters can successfully resist the invasion of defectors and, due to adaptive migration, can expand. On the contrary, for high migration speed, e.g.,  $p=0.86$ , the invasion is too strong to be defended, resulting in extinction of cooperators. The present scenario is analogous to water confinement by a dam: if the dam is sufficient solid, water can be contained; otherwise, the dam breaks and water is lost. There will be no intermediate state between the two states. This explains the sharp transition in Fig. 5(b).

## VI. CONCLUSION

In summary, we have proposed the mechanism of adaptive migration to achieve effective cooperation in evolutionary games occurring on spatially extended scales. Adaptive migration can be realized based solely on local information obtainable through game interactions, which may be less restricted than the recently proposed success-driven migration mechanism [19]. Our main finding is the existence of some optimal degree of migration (or population density) for cooperation to be maximized, and this property appears to hold regardless of the type of games (e.g., SG or PDG). The optimal degree of migration depends on both the migration

speed and the density of empty sites. Our simulation results are consistent with analysis based on the mean-field theory. We have gained a qualitative understanding by examining the evolution of spatial patterns, revealing that an appropriate combination of the density of empty sites and migration speed can lead to the aggregation of cooperation clusters that play the key role in promoting and sustaining cooperation. Our computations have indicated that adaptive migration can be effective to counter erosion of defectors embedded inside cooperator clusters. Another finding is the outbreak of cooperation from an environment of defectors in a wide range of values of the density of empty sites. These results suggest

adaptive migration as a general mechanism for the emergence of cooperation in complex dynamical systems.

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