Eur. Phys. J. B (2022) 95:67
https://doi.org/10.1140/epjb/s10051-022-00327-8

THE EUROPEAN
PHYSICAL JOURNAL B

Regular Article - Statistical and Nonlinear Physics

Environment-driven migration enhances cooperation in evolutionary public goods games

Shilin Xiao[1], Liming Zhang[1,a], Haihong Li[1], Qionglin Dai[1,b], and Junzhong Yang[1]

[1] School of Science, Beijing University of Posts and Telecommunications, Beijing 100876, China

Received 19 January 2022 / Accepted 28 March 2022 / Published online 10 April 2022

Abstract. Migration plays a critical role in the evolution of cooperation under the framework of evolutionary game theory. Previous studies have demonstrated that individuals might make their migration decisions based on various information, for example, their current cooperative environments, potential advantages of new places, and their own aspirations. In reality, people may perceive environment information and make decisions based on these information. In this paper, we introduce an environment-driven migration into evolutionary public goods games which are carried out on a two-dimensional plane, where individuals decide whether to migrate according to the probabilities determined by the differences between the local and global cooperative environments. We find that such an environment-driven migration can effectively enhance cooperation. Furthermore, there exists an optimal migration noise that leads to a highest cooperation level. In addition, we also find that appropriate moving speeds and migration tendencies, as well as relatively low population densities in the model are more favorable to the evolution of cooperation.

1 Introduction

As a common behavior of living creatures, migration can be observed in a variety of groups from micro organism population to human society [1,2]. In the microbial world, microscopic organisms seek areas with higher concentrations of nutrients. Animals generally migrate for adequate food or suitable habitats. In human society, people migrate for different purposes, such as better living environments, richer resources, more working opportunities and so on. The effects of migration in social dynamics have received ample attention in a wide range of research fields, including microbiology [3], ecology [4], climate [5], and social science [6,7]. Notably, previous studies have demonstrated that migration plays an important role in the evolution of cooperation [8–11].

Cooperation is a fascinating manifestation of collective behavior in the real world. Over the past decades, the issue how to understand and explain the emergence and maintenance of cooperation in a population consisting of selfish individuals has been a hot topic [12–14]. Evolutionary game theory provides a powerful theoretical framework to study the evolution of cooperation [15–17]. In evolutionary games, the interactions between or among individuals are described by fundamental game models. As one of the most widely used paradigmatic games, the public goods game (PGG) characterizes appropriately the situation of contradiction between individual and group benefits, in which the group benefits can reach the maximum if all the members choose cooperation whereas rational individuals prefer to pursue higher individual profits by escaping cooperation cost. A large number of mechanisms have been proposed in spatial PGGs to support the boom of cooperators [14,18–20], such as punishment [21–25], reward [26–30] and individual migration [31,32].

Under the framework of evolutionary games, migration of population located on different spatial structures has been investigated in recent years. Vainsteim et al. [8,33] in their early works investigated spatial evolutionary games on square lattice with empty sites and found that the "always-move" rule can enhance cooperative behavior. Since then, the effects of migration on cooperation have been studied on a variety of spatial structures, including square lattice [34,35], complex networks [36,37], continuous plane [31,38,39], as well as interdependent networks [40,41]. Meanwhile, migration mechanisms driven by various factors have been proposed by taking accounts of different motivations. Helbing and Yu [42,43] proposed the success-driven migration based on "test interactions". Their results show that success-driven motion can promote cooperation to a great extent. Buesser et al. [44] introduced the opportunistic migration into spatial evolutionary games, which is also based on the payoff calculation for trial positions. The expectation-driven migration was considered by Wu et al. [45]. In their model, individuals are assumed to make decisions whether to migrate based on the comparisons of their expectations and the real cooperativeness of this neighborhood. Chen

---

[a] e-mail: zhanglm@bupt.edu.cn (corresponding author)
[b] e-mail: qldai@bupt.edu.cn (corresponding author)

et al. [46] proposed the risk-driven migration, which depends on the difference between the actual contributions in the common pool and the declared target. Cardinot et al. [47] found that abstention in prisoner's dilemma game can promote cyclic dominance behaviour of strategies, which provides cooperators an alternative way to survive. Furthermore, the effects of hybrid mechanisms mixing different migration driving factors have also been studied [48]. Besides the inducement of migration, moving speed is also an important factor in migration models and influences the evolution of cooperation greatly. In [37,49], the researchers considered payoff-related migration and found that payoff-dependent moving speed improves cooperation effectively when compared with the case that all the individuals migrate with the same speed. Meanwhile, different migration ways including random migration [38,50–52] and directional migration [31,53] have been widely studied.

The environment often plays important roles in the evolution of social and biological systems, and environment based microscopic dynamics has been taken into considerations in several works [54,55]. In some cases, less information is required by individuals to make decisions, including whether to migrate or where to migrate, whereas in other cases more information is needed. For example, for entirely random migration on square lattice, individuals only need to know whether there exist empty sites [56–58]. In contrast, with regard to directional migration, individuals need to be aware of more information. In the migration based on "test interactions" [42], individuals need to know the strategies of the empty site's neighbors. As another example, in [31], individuals need to observe neighbors' moving directions and then determine their own orientation. We notice that, in most previous studies, it is assumed that individuals only have information of their local environments. In fact, the creature may perceive the external environment information and make decisions based on comparison. For example, during the dry season, the elephants may migrate to the range in memory where more permanent sources of water are available, which makes possible the continuation of race. In human society, the modern communication industry enables individuals to acquire more comprehensive information in larger scales from local environments to global ones, which contribute to migrant work, study abroad and immigration. Besides, the progress of communication technology often brings great changes to many industries and promotes the progress of human civilization. Considering these, we introduce a novel migration mechanism into evolutionary PGGs which are carried out on a two-dimensional plane. In particular, we assume that, individuals decide whether to migrate with the probabilities determined by the comparison between their local and global cooperative environments. We focus on how such an environment-driven migration affects the evolution of cooperation in evolutionary PGGs.

The rest of this paper is organized as follows. We describe in detail the model of the evolutionary PGGs involving the environment-driven migration in Sect. 2. Then, we present numerical simulation results and discussion in Sect. 3. Finally, we summarize this work in Sect. 4.

2 Model

We consider an off-lattice model in which N individuals can move continuously in a square region of length L with periodic boundary conditions. The positions of these individuals, denoted by $\vec{r}_i(t) = (x_i(t), y_i(t))$ with $0 \leq x_i(t), y_i(t) \leq L$, change with time according to prescribed rules, which leads to a dynamic interaction network among individuals once a interaction radius R is given. We set $L = 10$ unless specified. Initially, individuals are randomly distributed in the square region, and each individual is initialized as a cooperator or a defector with equal probability. We denote the strategy of i by s_i, and $s_i = 1$ means i is a cooperator whereas $s_i = 0$ means i is a defector.

A Monte Carlo (MC) step includes the following elementary procedures:

(1) Interaction. Each individual i plays PGGs organized by himself and by all his neighbors. The position of individual i at time step t is denoted by $\vec{r}_i(t)$. Define the distance between individuals i and j to be $\Delta_{ij}(t) = \sqrt{\Delta x_{ij}^2 + \Delta y_{ij}^2}$ with $\Delta x_{ij} = \min\{\mid x_i(t) - x_j(t) \mid, L - \mid x_i(t) - x_j(t) \mid\}$ and $\Delta y_{ij} = \min\{\mid y_i(t) - y_j(t) \mid, L - \mid y_i(t) - y_j(t) \mid\}$. Then, the neighborhood set of individual i at t, $\Omega_i(t)$, is defined as

$$\Omega_i(t) = \left\{ j \middle| \Delta_{ij}(t) < R, i \neq j \right\}, \tag{1}$$

where R is the interaction radius and $0 \leq R \leq L/2$. Moreover, we define the mean group size $\bar{k}$ as $\bar{k} = N\frac{\pi R^2}{L^2}$, which describes the average number of individuals within the interaction radius on the plane [59].

We adopt a traditional version of PGG [60] for the interactions among the population. Cooperators invest a cooperation cost c in the public pool, while defectors do nothing. The total investments will be multiplied by a synergy factor r ($r > 1$), and then the group income is distributed evenly to each member no matter whether he invests or not. If all the members choose to invest in the public pool, the group benefits will reach the maximum. However, the selfish members choosing defection can get higher payoffs by escaping the cost of investment. In this way, individual i's payoff obtained from one single PGG l can be calculated by

$$P_{i,l} = \begin{cases} \frac{rcn_{\mathrm{C}}}{n_{\mathrm{C}}+n_{\mathrm{D}}} - c, & \text{if } s_i(t) = 1, \\ \frac{rcn_{\mathrm{C}}}{n_{\mathrm{C}}+n_{\mathrm{D}}}, & \text{if } s_i(t) = 0, \end{cases} \tag{2}$$

where $s_i(t)$ represents i's strategy at time step t, the cooperation cost c is fixed to be $c = 1$, and n_{C} and n_{D} denote the number of cooperators and defectors in all the members of the PGG l, respectively. Therefore, the accumulated payoff of individual i obtained from all the PGGs he participates in can be given by

$$P_i = \sum_{l \in M_i} P_{i,l}, \tag{3}$$

where M_i represents the set of all PGGs that individual i participates in.

(2) Strategy imitation. After interactions and payoff accumulations, each individual i randomly chooses one individual j from his neighborhood Ω_i, and then adopts j's strategy in the next time step with the probability conforming to the Fermi function [61]:

$$w_{s_i \leftarrow s_j} = \frac{1}{1 + \mathrm{e}^{-(P_j - P_i)/\alpha}}, \tag{4}$$

where α indicates the noise intensity in strategy imitation, characterizing the possibility of the irrational choices of individuals.

(3) Migration. Different from most of previous works, we assume that each individual can not only perceive his own local cooperative environment but also acquire the global cooperation information. By comparing the local and global environments, each individual decides whether to migrate or not with a probability determined by the difference. In particular, for each individual i, we measure the local cooperative environment by the fraction of cooperators in his neighborhood, defined by $f_{i,\mathrm{C}} = \frac{n_{\mathrm{C},\Omega_i}}{|\Omega_i|}$, in which n_{C,Ω_i} is the number of cooperators in i's neighborhood set and $|\Omega_i|$ represents the total number of members in the set Ω_i. On the other hand, the global cooperative environment is given by the frequency of cooperators in the whole population, defined by $f_{\mathrm{C}} = \frac{N_{\mathrm{C}}}{N}$, where N_{C} is the number of cooperators in the population. If $f_{i,\mathrm{C}} > f_{\mathrm{C}}$, it means that i's local environment is currently better than the global one. In the view of the realistic consideration, the individual on this occasion would like to stay where he is instead of migrating to somewhere else. Contrarily, if the global environment is superior to the local environment, the individual would prefer to migrate away from the current neighborhood to seek better environment. Based on these, we assume that the migration probability μ_i is given by

$$\mu_i = \frac{\mu_0}{1 + e^{-(f_{\mathrm{C}} - f_{i,\mathrm{C}})/\beta}}, \tag{5}$$

in which μ_0 represents the migration tendency for the whole population and β represents the noise intensity in migration. Once individual i decides to migrate, he will update his position in next step according to the following equation

$$\vec{r}_i(t+1) = \vec{r}_i(t) + \vec{v}_i(t) \triangle t, \tag{6}$$

where $\triangle t$ is equal to 1 between two successive MC steps and $\vec{v}_i$ is the migration velocity including moving speed and direction. For simplicity, we assume that the moving speed v is same for all individuals and remains constant throughout the evolution while the migration direction is random. Here, there are two factors influencing the neighborhood of an individual. The one is, he might adjust the interacting neighbors by migration to get a better local environment. The other is, the neighbors are determined by the interaction radius R. We further introduce a parameter γ, defined by $\gamma = v/R$, to normalize the moving speed. In addition, if one individual does not have any neighbors at the current time step, he will migrate directly.

We carry out numerical simulations for the model and mainly focus on the cooperation level f_{C}, which is characterized by the frequency of cooperators in the population. The total simulation time is 10^5 MC steps and the steady states are averaged over the last 5000 steps. Each data point is obtained from averaging over 200 independent realizations with different initial conditions.

3 Results and discussion

We start from the impact of the migration noise β on the evolution of cooperation. As mentioned above, β characterizes the noise intensity in the individuals' decisions of migration. Small β means that individuals can decide whether to migrate or not based on environment comparison with a high rational level. Contrarily, in the case of large β, migration becomes random and environment comparison does not play much role. Figure 1a shows the cooperation level f_{C} against β at several different synergy factors r. For small r, cooperators could not survive no matter what the value of β is. For intermediate r, The curves show a non-monotonous noise dependence of cooperation level. We can find that f_{C} first increases and then decreases with the increase of β. There exists an optimal β at which the cooperation level reaches the highest value. Such a non-monotonous characteristics is actually a general behavior and has been reported in early works [34,62]. For a rather large r which is conducive to cooperation, an extremely high cooperation level could be obtained at small β, while f_{C} declines gradually at relatively large β. Meanwhile, we show the critical value of r (denoted by r_{c}), under

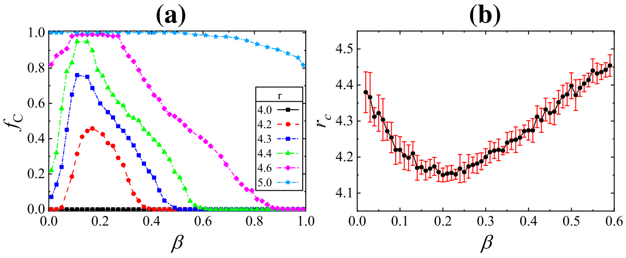

Fig. 1 **a** The frequency of cooperators f_{C} as a function of the migration noise β at several different r. **b** The critical synergy factor r_{c} supporting the survival of cooperators as a function of the migration noise β. The error bars display the standard deviation of 200 independent realizations. Other parameters: $\mu_0 = 0.1$, $\alpha = 0.1$, $\gamma = 0.5$, $\bar{k} = 5$

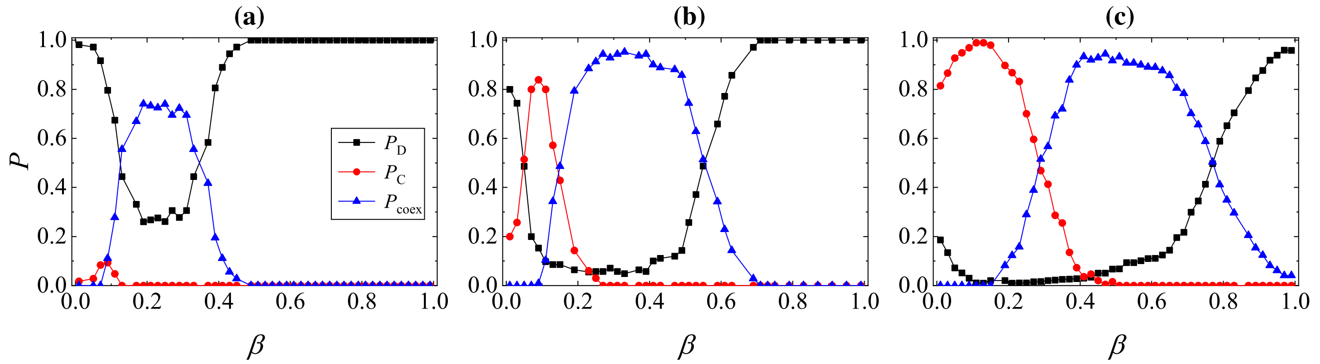

Fig. 2 The probabilities of three steady states, full-cooperator (full-C), full-defector (full-D) and coexistence of cooperators and defectors, denoted by P_C, P_D, and P_{coex}, respectively, as a function of the migration noise β at several different r. **a** $r = 4.2$, **b** $r = 4.4$, **c** $r = 4.6$. The probabilities are obtained from counting the frequencies in total 200 realizations with different initial conditions. Other parameters: $\mu_0 = 0.1$, $\alpha = 0.1$, $\gamma = 0.5$, $\bar{k} = 5$

which cooperation is certain to go extinct, as a function of β in Fig. 1b. As one can see, r_c drops first and then rises with β increasing. The minimum r_c appears near $\beta = 0.2$. It means that, at the optimal β, a relatively small synergy factor could support the survival of cooperators.

It should be pointed out that, the cooperation levels in Fig. 1 are obtained from averaging over 200 realizations with different random initial conditions. When we investigate one specific evolution process, we find that, different realizations may lead to different steady states. For this model, there are three possible steady states, full-cooperator (full-C), full-defector (full-D) and coexistence of cooperators and defectors. We denote the probabilities of these three states appearing in the total 200 realizations by P_C, P_D, and P_{coex}, respectively. Figure 2 shows these three probabilities against β at different r. As shown in Fig. 2, at small β, bistable states including full-C and full-D might be reached whereas there is no coexistence. With the increase of β, P_C increases whereas P_D decreases. Then the coexistence may occur, and the three states appear with different possibilities. However, with the further increase of β, P_C begins to decrease. When P_C goes down to 0, full-C state disappears and only the coexistence and full-D states remain. When β continues to increase, P_{coex} first increases and then decreases, whereas P_D changes in the opposite way. Thus, a plateau and a valley are formed in P_{coex} and P_D, respectively. When β is large enough, the population enters full-D state definitely. Moreover, when comparing the results for different r, we can find that, large r leads to lower P_D and higher P_C as a whole, and the valley of P_D and the plateau of P_C both become wider.

Here, we offer an intuitive explanation on Fig. 2. For small β rendering individuals rational, once cooperators adjoin each other, they will tend to keep still, which impedes the expansion of cooperators in the plane. In contrast, rational defectors will invade cooperators more aggressively with smaller β. Compared with the migration conducted on graph where defectors can only move through the connections of the underlying networks [33,56], here defectors might migrate to any directions in the plane, making it easier to invade cooperators. Both these influences are unfavorable to the evolution of cooperation, and thus P_C is very low at small β. When β increases, the cooperators who neighbor with cooperators are also possible to move. Due to the random direction of migration, there may be two possible cases for the moving of cooperators located at the boundary between cooperators and defectors. One is moving toward cooperator-clusters (C-clusters), which makes the C-clusters more compact and therefore enhances network reciprocity. The other is moving outward, resulting in the possible expansion of C-clusters in the plane. These lead to the increase of P_C and the decrease of P_D. With the further increase of β, the migration of the cooperators becomes frequent, which weakens the compactness of C-clusters

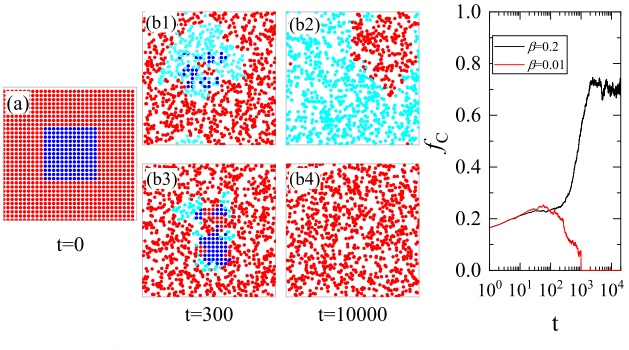

Fig. 3 **a** A prepared initial condition in which the individuals are arranged as a lattice on the plane with a square center filled with cooperators (blue) and the rest are defectors (red). **b1**–**b4** Snapshots of the distributions of individuals as well as their strategies on the plane. Cyan is for the cooperators who have moved, and blue for those who keep at the initial positions. **b1**, **b2** $\beta = 0.2$, **b3**, **b4** $\beta = 0.01$. **c** Time series of f_C for two different β, corresponding to those in (b1,b2) and (b3,b4), respectively. Other parameters: $N = 1024$, $L = 10$, $\mu_0 = 0.1$, $\alpha = 0.1$, $\gamma = 0.5$, $\bar{k} = 5$, r=4.4

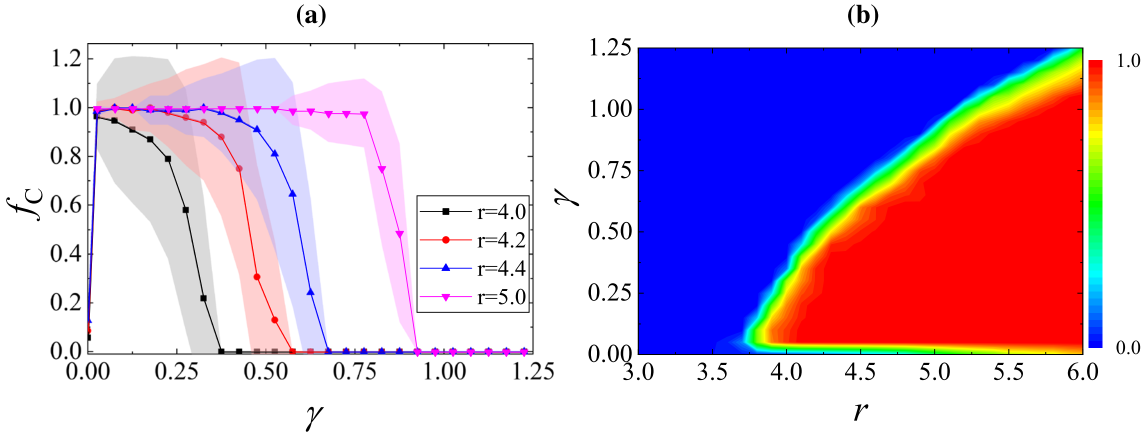

Fig. 4 **a** The frequency of cooperators f_C against γ at several different r. Points refer to the mean values of 200 independent realizations and the color strips represent the standard deviation. **b** The contour plot of f_C in the $\gamma - r$ plane. Other parameters: $\mu_0 = 0.1$, $\alpha = \beta = 0.1$, $\bar{k} = 5$

and therefore leaves space for the coexistence of cooperators and defectors. Then, P_{coex} increases and P_C decreases. When β continues to increase, the random and frequent migration will destroy C-clusters, leading to the decrease of P_{coex} and the increase of P_D.

To verify the above explanation and provide a clear picture for the evolution of cooperation at different β, we simulate the model with a prepared initial condition shown by Fig. 3a, where the individuals are arranged as a lattice on the plane with a square center filled with cooperators and the rest by defectors. Two different values of β are considered. One is a relatively large β, $\beta = 0.2$, at which coexistence appears with an extremely high probability in the steady states. The other is a small one, $\beta = 0.01$, at which only full-C and full-D can be reached in the steady states. We choose one realization for each β, and show the snapshots at representative times in Fig. 3b1–b4 and the corresponding time series of f_C in Fig. 3c. For $\beta = 0.2$, individuals decide whether to migrate or not with a relatively large noise density. As shown in Fig. 3b1, b2, cooperators form clusters on the plane, and the survive and expansion of cooperators owes to the network reciprocity. Though defectors might invade C-clusters during the evolution, cooperators can coexist with defectors and even exceed defectors in number in the steady states. When $\beta = 0.01$, individuals migrate based on environment comparison with a high rational level. The individuals in C-clusters tend to stay still because of their cooperative local environment. As shown in Fig. 3b3, there still exist some cooperators inside C-clusters keeping unmoved at $t = 300$. This factor leads to firm C-clusters which facilitate the evolution of cooperation. However, it is worthy of noticing that, small β can also accelerate the migration of defectors and afford the opportunities for them to invade C-clusters. Thus, we can also see that, in Fig. 3b3, C-clusters are divided into two separate parts by invasive defectors. These two competitive effects of small β result in the final full-C or full-D state. Figure 3b3, b4 provides a realization in which the final state is full-D. From these, we know that small β may destroy cooperation by prompting defectors to migrate, whereas large β makes individuals migrate in a random way and environment comparison does not work due to strong noise. These two factors jointly lead to the optimization of f_C at an intermediate β.

Next, we discuss the effects of moving speed γ on the evolution of cooperation. Since $\gamma = v/R$, zero γ suggests the interaction network between individuals is stationary while sufficient large γ suggests a well-mixed population due to the fast migration. Therefore, γ actually controls the time scale of the migration. Figure 4a shows the cooperation level f_C against γ at several different r. When the migration is not involved in the evolutionary dynamics ($\gamma = 0$), the individuals stay still on the plane and the cooperation levels are quite low. Once γ increases and does not equal to zero, f_C climbs to a peak quickly. Then, f_C decreases with the further increase of γ. Meanwhile, we present the standard deviations of the average f_C for different realizations. It can be found that, the fluctuations of f_C are enhanced around the sharp decline of f_C. Furthermore, we give the contour diagram to present the overall results in the $\gamma - r$ parameter plane. When r is small, no matter whether individuals move or not, cooperators can not be survived. When r exceeds the critical value, an intermediate range of γ can significantly promote cooperation.

Furthermore, we study the cooperation level f_C as a function of the synergy factor r at different migration tendency μ_0 and show the results in Fig. 5. For comparison, we also show the results at $\mu_0 = 0$ where there is no migration. At relatively small r, though f_C is very low, cooperators would not disappear. It differ from the square lattice case where cooperators die out at $r_c = 3.745$ for imitation noise value $\alpha = 0.1$ [63]. Here the model is an off-lattice one where players can be anywhere in the square region, and a dynamic one. As a result, there may exist some cooperators who

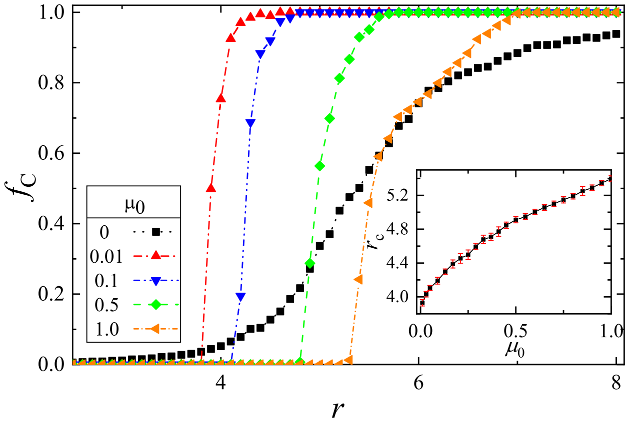

Fig. 5 The cooperation level f_C as a function of the synergy factor r at several different μ_0. The inset shows the critical synergy factor r_{rmc} supporting the survival of cooperators against μ_0, μ_0 starting from 0.01 to 1. Other parameters: $\alpha = \beta = 0.1$, $\gamma = 0.5$, $\bar{k} = 5$

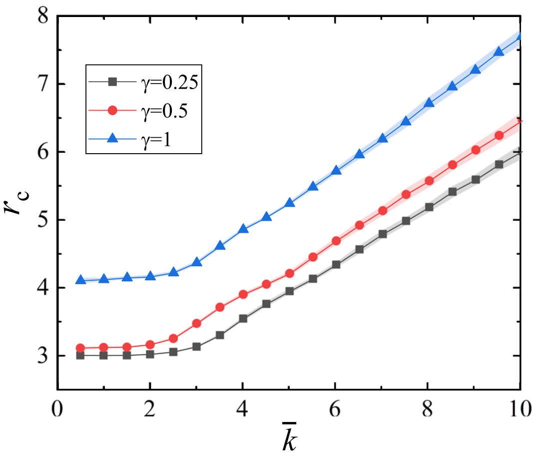

Fig. 6 The critical synergy factor r_c supporting the survival of cooperators as a function of the mean group size $\bar{k}$. Here, we adjust $\bar{k}$ by changing N while keeping $L = 10$ and $R = 0.5$. Other parameters: $\mu_0 = 0.1$, $\alpha = \beta = 0.1$

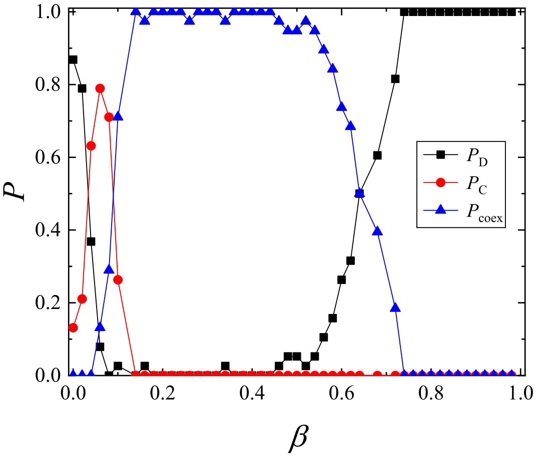

Fig. 7 The probabilities P_C, P_D, and P_{coex} in dependence on the migration noise β for $N = 2000$. Other parameters: $r = 4.4$, $L = 10$, $\mu_0 = 0.1$, $\alpha = 0.1$, $\gamma = 0.5$, $\bar{k} = 5$

are initialized geographically to be isolated from defectors. With the assistant of the migration rule Eq. (5), these cooperators tend to form cooperator clusters to avoid being invaded by defector. This effect can be more pronounced in sparse populations [64,65]. Nevertheless, they can not be survived at non-zero μ_0. It means that, the migration based on environment comparison is unfavorable for cooperation at small r. However, once r exceeds a critical value, f_C goes up rapidly with the increase of r, and cooperation is enhanced significantly by the migration. In addition, from the inset of Fig. 5, we can find that, r_c increases with the increase of μ_0. It implies that, although the migration could greatly promote cooperation, a low but non-zero migration tendency for the whole population is more beneficial for the evolution of cooperation.

Since the individuals are distributed on a two-dimensional plane, the size of the group is also a crucial parameter which influences the evolution of cooperation. We show the critical value of the synergy factor r_c against $\bar{k}$ in Fig. 6. One can see that, when $\bar{k}$ is in a range of small values, r_c is not sensitive to the change of $\bar{k}$. When $\bar{k}$ is larger than about 2.5, r_c increases with $\bar{k}$ increasing. It means that, when the population becomes dense to some extent, high synergy factor r is needed for the maintenance of cooperation in this model.

Besides, the system size has been found to have strong effects on the evolution of cooperation, especially for the probabilities of asymptotically stable states [66–68]. The simulations above are carried out for $N = 1000$. To examine the effects of the system size, we consider $N = 2000$ and investigate the dependence of P_C, P_D, and P_{coex} on β. The results are presented Fig. 7. Clearly, these probabilities against β are quantitatively different from those in Fig. 2b. For example, the ranges of parameter β leading to the valley of P_D and the peak of P_{coex} become wider and the minimum (maximum) value is further decreased (increased), and for nonzero P_C the range of β is compressed. Nevertheless, we can find that the overall trends of P_C, P_D, and P_{coex} with respect to β remain the same qualitatively.

Then, we also simulate the model with average individual payoff case. The gain of an individual i involved in the comparison in Eq. (4) is replaced by $\bar{P}_i = \frac{P_i}{M_i}$ where P_i is the accumulative payoff defined by Eq. (3) and M_i denotes the number of groups that i belongs to. From Fig. 8a, we can also observe the similar non-monotonous noise dependence of the cooperation level described in Fig. 1a. Figure 8b shows that the nonzero μ_0 curves shift rightward in comparison with Fig. 5 while the curve of $\mu_0 = 0$ keeps unchanged, which indicates that applying the average payoff is less effective in promoting cooperation. Nevertheless, similar to what we have discussed in Fig. 5, once r exceeds a certain threshold, migration is preferable to the case of no migration in the promotion of cooperation. The results indicate that our model is robust to the payoff types in the promotion of cooperation.

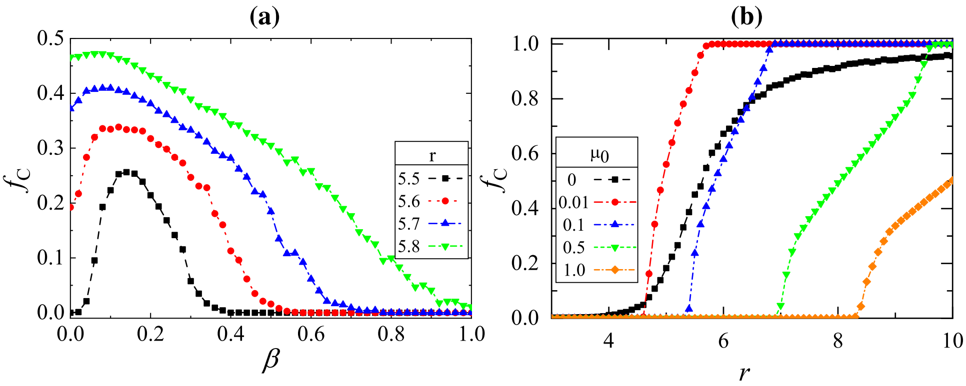

Fig. 8 Fraction of cooperators f_C in dependence on β in **a** and r in **b** in the case of average payoff. We set $\mu_0 = 0.1$ in **a** and $\beta = 0.1$ in **b**. For both, $N = 1000$, $L = 10$, $\alpha = 0.1$, $\gamma = 0.5$ and $\bar{k} = 5$

4 Conclusion

To summarize, we study the effects of environment-driven migration in evolutionary public goods games on a two-dimensional plane, in which individuals could perceive both their own local cooperative environment and the global cooperative environment, and then make decisions of migration based on environment comparison. In the model, we introduce a parameter β to describe the noise intensity in the migration decision. By numerical simulations, we find that, the migration based on environment comparison could promote cooperation significantly. Moreover, there exists an optimal β which leads to a highest cooperation level. We also find that, different steady states may be obtained from different realizations with independent initial conditions. We further simulate the model with a prepared initial condition, and show the competitive factors that lead to different outcomes by investigating the snapshots of strategy patterns during the evolution. Based on these, we present a brief explanation for the optimization of the cooperation level by the noise intensity β. Moreover, we investigate the effects of moving speed, the moving tendency and the mean group size on cooperation. At last, we verify the robustness of the model to the system size and the average payoff case. We find the conclusions keep unchanged qualitatively. The extensions of this work may consider the cost of accessing the environment information or heterogeneous time scales of the two behaviors. We hope this work could deepen the understanding of the effects of migration on the evolution of cooperation, especially in the case that the individuals can perceive environments with certain rationalities and make decisions based on the environment information.

Acknowledgements This work was supported by the National Natural Science Foundation of China under Grant no. 11805021 and the BUPT Excellent Ph.D. Students Foundation under Grant no. CX2021226.

Author contributions

SX and LZ: conceptualization, methodology, investigation, writing-original draft. HL: conceptualization, methodology, visualization, Software. QD: writing-original draft, formal analysis, funding acquisition, validation. JY: validation, supervision.

Data Availability Statement This manuscript has no associated data or the data will not be deposited. [Authors' comment: The results are obtained mainly through numerical simulation, and all the related data have been shown in the figures of the article.]

References

1. H. Dingle, *Migration: The Biology of Life on the Move* (Oxford University Press, Oxford, 2014)
2. M.J. Greenwood, Human migration: theory, models, and empirical studies. J. Reg. Sci. **25**(4), 521–544 (1985)
3. A.J. Wolfe, H.C. Berg, Migration of bacteria in semisolid agar. Proc. Natl. Acad. Sci. **86**(18), 6973–6977 (1989)
4. I. Newton, *The Migration Ecology of Birds* (Elsevier, Amsterdam, 2010)
5. O. Brown, *Migration and Climate Change* (United Nations, New York, 2008)
6. D. Brockmann, L. Hufnagel, T. Geisel, The scaling laws of human travel. Nature **439**(7075), 462–465 (2006)
7. M.C. Gonzalez, C.A. Hidalgo, A.L. Barabasi, Understanding individual human mobility patterns. Nature **453**(7196), 779–782 (2008)
8. M.H. Vainstein, A.T. Silva, J.J. Arenzon, Does mobility decrease cooperation? J. Theor. Biol. **244**(4), 722–728 (2007)
9. E.A. Sicardi, H. Fort, M.H. Vainstein, J.J. Arenzon, Random mobility and spatial structure often enhance cooperation. J. Theor. Biol. **256**(2), 240–246 (2009)
10. F. Funk, C. Hauert, Directed migration shapes cooperation in spatial ecological public goods games. PLoS Comput. Biol. **15**(8), e1006948 (2019)
11. S. Dhakal, R. Chiong, M. Chica, R..H. Middleton, Climate change induced migration and the evolution

of cooperation. Appl. Math. Comput. **377**(125), 090 (2020)

12. A.M. Colman et al., *Game Theory and its Applications in the Social and Biological Sciences* (Psychology Press, Hove, 1995)
13. R.A. Johnstone, A.M. Rodrigues, Cooperation and the common good. Philos. Trans. R. Soc. B Biol. Sci. **371**(1687), 20150086 (2016)
14. M. Perc, J.J. Jordan, D.G. Rand, Z. Wang, S. Boccaletti, A. Szolnoki, Statistical physics of human cooperation. Phys. Rep. **687**, 1–51 (2017)
15. M.A. Nowak, R.M. May, Evolutionary games and spatial chaos. Nature **359**(6398), 826–829 (1992)
16. J. Hofbauer, K. Sigmund et al., *Evolutionary Games and Population Dynamics* (Cambridge University Press, Cambridge, 1998)
17. G. Szabó, G. Fath, Evolutionary games on graphs. Phys. Rep. **446**(4–6), 97–216 (2007)
18. M. Perc, A. Szolnoki, Coevolutionary games—a mini review. Biosystems **99**(2), 109–125 (2010)
19. M. Perc, P. Grigolini, Collective behavior and evolutionary games—an introduction. Chaos Solitons Fractals **56**, 1–5 (2013)
20. M. Perc, J. Gómez-Gardenes, A. Szolnoki, L.M. Floría, Y. Moreno, Evolutionary dynamics of group interactions on structured populations: a review. J. R. Soc. Interface **10**(80), 20120997 (2013)
21. L. Liu, X. Chen, A. Szolnoki, Evolutionary dynamics of cooperation in a population with probabilistic corrupt enforcers and violators. Math. Models Methods Appl. Sci. **29**(11), 2127–2149 (2019)
22. M. Perc, A. Szolnoki, Self-organization of punishment in structured populations. New J. Phys. **14**(4), 043013 (2012)
23. X. Chen, A. Szolnoki, M. Perc, Competition and cooperation among different punishing strategies in the spatial public goods game. Phys. Rev. E **92**(1), 012819 (2015)
24. X. Chen, A. Szolnoki, M. Perc, Probabilistic sharing solves the problem of costly punishment. New J. Phys. **16**(8), 083016 (2014)
25. B. Wu, H.J. Park, L. Wu, D. Zhou, Evolution of cooperation driven by self-recommendation. Phys. Rev. E **100**(4), 042303 (2019)
26. S. Wang, X. Chen, A. Szolnoki, Exploring optimal institutional incentives for public cooperation. Commun. Nonlinear Sci. Numer. Simul. **79**, 104914 (2019)
27. J. Liu, T. Li, W. Wang, N. Zhao, F. Hang, Impact of strategy-neutral rewarding on the evolution of cooperative behavior. Chaos Solitons Fractals **106**, 76–79 (2018)
28. J. Du, Redistribution promotes cooperation in spatial public goods games under aspiration dynamics. Appl. Math. Comput. **363**, 124629 (2019)
29. J. Du, L. Tang, Evolution of global contribution in multi-level threshold public goods games with insurance compensation. J. Stat. Mech. Theory Exp. **2018**(1), 0132403 (2018)
30. J. Du, B. Wang, Evolution of global cooperation in multi-level threshold public goods games with income redistribution. Front. Phys. **6**, 67 (2018)
31. L. Zhang, C. Huang, H. Li, Q. Dai, J. Yang, Effects of directional migration for pursuit of profitable circumstances in evolutionary games. Chaos Solitons Fractals **144**, 110709 (2021)
32. R. Cong, Q. Zhao, K. Li, L. Wang, Individual mobility promotes punishment in evolutionary public goods games. Sci. Rep. **7**(1), 1–9 (2017)
33. M.H. Vainstein, J.J. Arenzon, Disordered environments in spatial games. Phys. Rev. E **64**(5), 051905 (2001)
34. G. Szabó, J. Vukov, A. Szolnoki, Phase diagrams for an evolutionary prisoner's dilemma game on two-dimensional lattices. Phys. Rev. E **72**(4), 047107 (2005)
35. H. Guo, X. Li, K. Hu, X. Dai, D. Jia, S. Boccaletti, M. Perc, Z. Wang, The dynamics of cooperation in asymmetric sub-populations. New J. Phys. **22**(8), 083015 (2020)
36. W. Yu, Mobility enhances cooperation in the presence of decision-making mistakes on complex networks. Phys. Rev. E **83**(2), 026105 (2011)
37. H. Cheng, Q. Dai, H. Li, Y. Zhu, M. Zhang, J. Yang, Payoff-related migration enhances cooperation in the prisoner's dilemma game. New J. Phys. **13**(4), 043032 (2011)
38. S. Meloni, A. Buscarino, L. Fortuna, M. Frasca, J. Gómez-Gardeñes, V. Latora, Y. Moreno, Effects of mobility in a population of prisoner's dilemma players. Phys. Rev. E **79**(6), 067101 (2009)
39. Z. Xiao, X. Chen, A. Szolnoki, Leaving bads provides better outcome than approaching goods in a social dilemma. New J. Phys. **22**(2), 023012 (2020)
40. Z. Wang, A. Szolnoki, M. Perc, Evolution of public cooperation on interdependent networks: The impact of biased utility functions. EPL (Europhys. Lett.) **97**(4), 48001 (2012)
41. S. Nag Chowdhury, S. Kundu, M. Duh, M. Perc, D. Ghosh, Cooperation on interdependent networks by means of migration and stochastic imitation. Entropy **22**(4), 485 (2020)
42. D. Helbing, W. Yu, Migration as a mechanism to promote cooperation. Adv. Complex Syst. **11**(04), 641–652 (2008)
43. D. Helbing, W. Yu, The outbreak of cooperation among success-driven individuals under noisy conditions. Proc. Natl. Acad. Sci. **106**(10), 3680–3685 (2009)
44. P. Buesser, M. Tomassini, A. Antonioni, Opportunistic migration in spatial evolutionary games. Phys. Rev. E **88**(4), 042806 (2013)
45. T. Wu, F. Fu, Y. Zhang, L. Wang, Expectation-driven migration promotes cooperation by group interactions. Phys. Rev. E **85**(6), 066104 (2012)
46. X. Chen, A. Szolnoki, M. Perc, Risk-driven migration and the collective-risk social dilemma. Phys. Rev. E **86**(3), 036101 (2012)
47. M. Cardinot, C. O'Riordan, J. Griffith, A. Szolnoki, Mobility restores the mechanism which supports cooperation in the voluntary prisoner's dilemma game. New J. Phys. **21**(7), 073038 (2019)
48. B. Li, X. Zhao, H. Xia, Promotion of cooperation by hybrid migration mechanisms in the spatial prisoner's dilemma game. Physica A **514**, 1–8 (2019)
49. Y.S. Chen, H.X. Yang, W.Z. Guo, Promotion of cooperation by payoff-driven migration. Physica A **450**, 506–514 (2016)
50. A.I. Houston, Mobility limits cooperation. Trends Ecol. Evol. **8**(6), 194–196 (1993)

51. A. Cardillo, S. Meloni, J. Gómez-Gardenes, Y. Moreno, Velocity-enhanced cooperation of moving agents playing public goods games. Phys. Rev. E **85**(6), 067101 (2012)
52. A. Antonioni, M. Tomassini, P. Buesser, Random diffusion and cooperation in continuous two-dimensional space. J. Theor. Biol. **344**, 40–48 (2014)
53. H. Cheng, Q. Dai, H. Li, X. Qian, M. Zhang, J. Yang, Effects of directional migration on prisoner's dilemma game in a square domain. Eur. Phys. J. B **86**(4), 1–6 (2013)
54. A. Szolnoki, A. Antonioni, M. Tomassini, M. Perc, Binary birth-death dynamics and the expansion of cooperation by means of self-organized growth. EPL (Europhys. Lett.) **105**(4), 48001 (2014)
55. D. Bazeia, M. Ferreira, B. de Oliveira, A. Szolnoki, Environment driven oscillation in an off-lattice May-Leonard model. Sci. Rep. **11**(1), 1–8 (2021)
56. L.L. Jiang, W.X. Wang, Y.C. Lai, B.H. Wang, Role of adaptive migration in promoting cooperation in spatial games. Phys. Rev. E **81**(3), 036108 (2010)
57. M.H. Vainstein, J.J. Arenzon, Spatial social dilemmas: dilution, mobility and grouping effects with imitation dynamics. Physica A **394**, 145–157 (2014)
58. Y. Li, H. Ye, Effect of migration based on strategy and cost on the evolution of cooperation. Chaos Solitons Fractals **76**, 156–165 (2015)
59. Y. Li, H. Sun, W. Han, W. Xiong, Evolutionary public goods game on the birandom geometric graph. Phys. Rev. E **101**(4–1), 042303 (2020)
60. J.O. Ledyard, *2. Public Goods: A Survey of Experimental Research* (Princeton University Press, Princeton, 2020), pp. 111–194
61. G. Szabó, C. Tőke, Evolutionary prisoner's dilemma game on a square lattice. Phys. Rev. E **58**(1), 69 (1998)
62. J. Vukov, G. Szabó, A. Szolnoki, Cooperation in the noisy case: Prisoner's dilemma game on two types of regular random graphs. Phys. Rev. E **73**(6), 067103 (2006)
63. A. Szolnoki, M. Perc, G. Szabó, Topology-independent impact of noise on cooperation in spatial public goods games. Phys. Rev. E **80**(5), 056109 (2009)
64. Z. Wang, A. Szolnoki, M. Perc, Percolation threshold determines the optimal population density for public cooperation. Phys. Rev. E **85**(3), 037101 (2012)
65. Z. Wang, A. Szolnoki, M. Perc, If players are sparse social dilemmas are too: importance of percolation for evolution of cooperation. Sci. Rep. **2**(1), 369 (2012)
66. T. Reichenbach, M. Mobilia, E. Frey, Mobility promotes and jeopardizes biodiversity in rock–paper–scissors games. Nature **448**(7157), 1046–1049 (2007)
67. A. Szolnoki, M. Perc, Competition of tolerant strategies in the spatial public goods game. New J. Phys. **18**(8), 083021 (2016)
68. A. Szolnoki, X. Chen, Alliance formation with exclusion in the spatial public goods game. Phys. Rev. E **95**(5), 052316 (2017)