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Enhancing cooperation through payoff-related inertia in networked prisoner's dilemma game

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ABSTRACT

In human societies and animal groups, individual behavior is often driven by self-interest, with actions typically avoided if they do not yield benefits. This paper focuses on payoff-related inertia, which describes the tendency of individuals to resist updating their strategies when faced with significant decreases in total payoffs compared to the last round. Through extensive simulations in both regular lattice and small-world networks, we find that individual inertia and its impact on cooperation evolves over time in Prisoner's Dilemma game. At early stages, increased inertia due to decreased payoffs reduces transition probabilities between cooperators and defectors, preventing rapid collective shifts to defection and allowing the formation of cooperative clusters. As these clusters form, payoff-related inertia facilitates the transition of defectors to cooperators, promoting the expansion and stability of cooperative groups. Furthermore, we find that the introduction of payoff-related inertia enhances cooperation levels more significantly in small-world networks compared to regular lattice. Our study sheds light on the mechanisms that foster cooperation among self-interested individuals, contributing to a deeper understanding of cooperative behavior. By examining the dynamic interplay between strategy-updating inertia and evolutionary cooperation, we provide insights into the conditions that promote the emergence and stability of cooperation in social dilemmas.

1. Introduction

The emergence of cooperative behaviors among selfish individuals presents a fascinating and challenging puzzle [1]. Within societies and ecosystems, cooperators selflessly sacrifice their personal interests for the collective benefit, while selfish defectors are more inclined to take. Consequently, defectors often appear to have a competitive advantage, being seemingly fitter and better positioned. According to Darwinism, the presence of altruistic individuals is at risk of being eliminated by defectors unless additional mechanisms supporting cooperation are taken into account [2]. This evolutionary puzzle of cooperation has garnered significant attention across interdisciplinary sciences, providing profound implications for understanding diverse phenomena, ranging from the origin of life to the evolution of human societies [3].

The Prisoner's Dilemma game (PD) serves as a powerful framework for studying the conflict between individual and group interests in social dilemmas, offering valuable insights into the evolution of cooperation among selfish individuals [4]. Within this framework, significant progress has been made in explaining the emergence, evolution, and spread of cooperation. Among the fundamental mechanisms supporting evolutionary cooperation, network reciprocity has emerged as a key factor [5,6], which explains why cooperative behaviors thrive in networked structures under various circumstances. Research in this area has shed light on the importance of various network features, such as degree distribution [7], static topology attributes [8–13], temporal or spatial features [14,15], interaction mechanisms within and across networks [16–21], and higher-order interactions [22–24], in shaping the evolution and prosperity of cooperation. Moreover, the influence of individual attributes and behavioral characteristics on the evolution of cooperation has been extensively explored within the framework of networked evolutionary games. These characteristics include social diversity [25], teaching activities [26], reproduction rate [27], learning abilities [28] or style [29], aspiration [30], rationality [31], mixing patten among groups [32], reputation [33–35], payoff control [36,37] and coevolutionary rules [38], all of which significantly support the persistence of cooperation.

In real-life scenarios, the behaviors of selfish individuals are closely tied to their prospective payoffs, which play a crucial role in driving their actions [39]. In evolutionary game, self-interested individuals typically pursue strategies that maximize their personal gains, which

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leads to a dynamic process of decision-making and strategy adaptation [15]. The inertia of strategy updating, which reflects the tendency of individuals to stick with their current strategies or the cost of strategy update, is a common characteristic of individuals in economic and social activities [40–42]. According to the interest-driven characteristics of selfish individuals, we assume that the inertia of individuals heavily influenced by the payoffs they achieve according to the strategies used in the games. In essence, if one individual updated its strategy in the last round and experienced an increase in it payoff, it indicates that the strategy updating is beneficial for its interest, and thus the individual may exhibit a larger inclination to change it strategy again. Conversely, those facing declining payoffs might become indifferent to further strategy updates, exhibiting a larger inertia for further strategy updating. This phenomenon of payoff-related inertia is pivotal in understanding how behaviors stabilize or change over time within a population.

Additionally, the behavior of strategy updating itself can impact the payoffs of individuals, creating a feedback loop that further complicates the evolutionary dynamics [27,28,43]. As individuals update their strategies based on prior payoffs, their new strategies influence future interactions and, consequently, future payoffs. This leads to a dynamic interplay between strategy-updating inertia and individual payoffs when payoff-related inertia is considered. Consequently, individual inertia evolves dynamically with changes in payoffs, making its impact on the system's evolution also dynamic. Understanding this the dynamic impact of payoff-related inertia on the system is crucial for unraveling the mechanisms that promote or hinder cooperative behavior in social dilemmas.

In this study, we aim to explore the effects of this dynamic interplay of strategy-updating inertia and individual payoffs on the evolutionary cooperation. We hypothesize that the inertia of one individual for strategy updating is influenced by the increase or decrease in their total payoffs compared to the previous round. Specifically, if the strategy update in the last step leads to a decrease in an individual's payoff, the individual has no incentive to update their strategy, resulting in increased inertia. Conversely, if the payoffs increased, individuals will be more proactive in updating their strategies, seeking to capitalize on new opportunities for greater gains. To systematically investigate the effects of this mechanism on evolutionary cooperation, we propose a modified Prisoner's Dilemma game. This model introduces a tuning parameter designed to control the influence of payoff-related inertia on the strategy-updating process, thereby allowing us to simulate and analyze various scenarios and their impact on cooperation dynamics. In addition, individual behavior can be propagated through social networks [3,44], and we use regular lattice and small-world networks as the structure of individual interactions to simulate the propagation of cooperation or defection.

By examining the evolutionary cooperation under the scheme of payoff-related inertia, we hope to shed light on how individual inertia factors influence the emergence and stability of cooperative behavior in networked evolutionary games. This study aims to incorporate more realistic assumptions about individual decision-making processes into theoretical models. Ultimately, our findings will have implications for understanding the evolution of cooperation, providing deeper insights into the conditions that foster or impede cooperative behavior. Additionally, this research offers practical insights into regulating cooperative behavior in various networked systems, such as social networks, economic markets, and ecological systems.

2. Model

In this paper, we employ a two-dimensional square lattice with periodic boundary conditions or a Watts–Strogatz small-world network [45]to represent the population structure, as done in previous works [3]. In this network, each node represents an individual, and the links between nodes represent pairwise interactions. We focus on studying a Prisoner's Dilemma game, in which each player can choose between two strategies: cooperation (C) and defection (D) in each round. During a single game, mutual cooperation results in a reward (P), mutual defection leads to punishment (P), a cooperator receives the sucker's payoff (S), and a defector gets the temptation (T) with the ranking $T > R > P > S$. This ranking implies that defection is the optimal choice for a selfish individual, regardless of the strategy of the opponent. For simplicity, we set $R = 1$, $P = 0$, $S = 0$, and $T = b$, with $1 < b < 2$, controlling the strength of the social dilemma [46].

In each evolutionary step, each player interacts with its nearest neighbors and collects payoffs from each interaction. After collecting payoffs, all players simultaneously update their strategies based on the accumulated payoff received in the current step. Specifically, at the t-th step, a player i randomly selects a player j from its nearest neighbors as a reference for strategy update. The probability that player i adopts player j's strategy depends on both the inertia of player i and the accumulated payoff difference ($\Delta P \equiv P_i(t) - P_j(t)$) between players i and j. The inertia $I_i(t)$ of strategy updating for player i is defined as $P_i(t-1) - P_i(t)$ if player i successfully updated its strategy at the $(t-1)$-th step; otherwise, $I_i(t)$ is set to 0 if player i gives up updating its strategy at the $(t-1)$-th step. The inertia emphasizes the loss in payoff compared with the previous round, which may be perceived by the individual as resulting from the strategy update. A larger $I_i(t)$ indicates a greater loss in payoff after the previous strategy update, making the player less likely to update their strategy in the current step. Conversely, a smaller $I_i(t)$ suggests a smaller loss in payoff, and if $I_i(t)$ is negative, it indicates an increase in payoff after the previous strategy update, motivating the player more inclined to learn from or adopt the strategy of the reference player during the current strategy-updating process. Consequently, player i learns the strategy of player j with a probability described by a Fermi function [46]

$$W_{ij} = \frac{1}{1 + e^{[\alpha I_i(t) + (1-\alpha)\Delta P]/K}}. \tag{1}$$

Here, K is the noise level, which lies in the range $[0, +\infty)$ and indicates the rationality degree of players. The inertia of an individual affects the probability of strategy update. According to Eq. (1), when other parameters are fixed, the greater the inertia of one player, the lower the probability of the strategy update. Meanwhile, the probability of strategy updating is also influenced by the payoff difference (ΔP) between players i and j, and a larger ΔP corresponds to a lower probability that player i learns the strategy of player j. The parameter α controls the relative weight of inertia ($I_i(t)$) and payoff difference (ΔP) in the strategy-updating process, with a higher α giving more weight to inertia.

The system evolves step by step from an initial state where each player is randomly assigned either strategy C or D, and the inertia of all players is set to 0 at the beginning. We use a two-dimensional square lattice and small-world network to imitate the population structure. For the square lattice, each node has four nearest neighbors. Based on the square lattice, we use the Watts–Strogatz model with a rewiring probability $p = 0.1$ to generate the small-world network [45]. For both types of networks, the average degree is 4. In all the simulation, we set the population size N to 100×100 and the noise level K to 0.1. The system evolves from the initial state to a dynamic stable state, and the cooperation level ρ_C is calculated by averaging the fraction of cooperators over the $2{\times}10^3$ time steps after a total of $2{\times}10^4$ in the stable state. Additionally, to account for the effect of initial randomness, we conduct 100 simulations with different initial strategy configurations and average the results.

3. Simulation and analysis

To explore the effects of payoff-related inertia on evolutionary cooperation, we present the cooperation density ρ_C as functions of α or b for both regular lattice and small-world networks in Fig. 1. One can find that the cooperation level ρ_C decreases monotonously with the

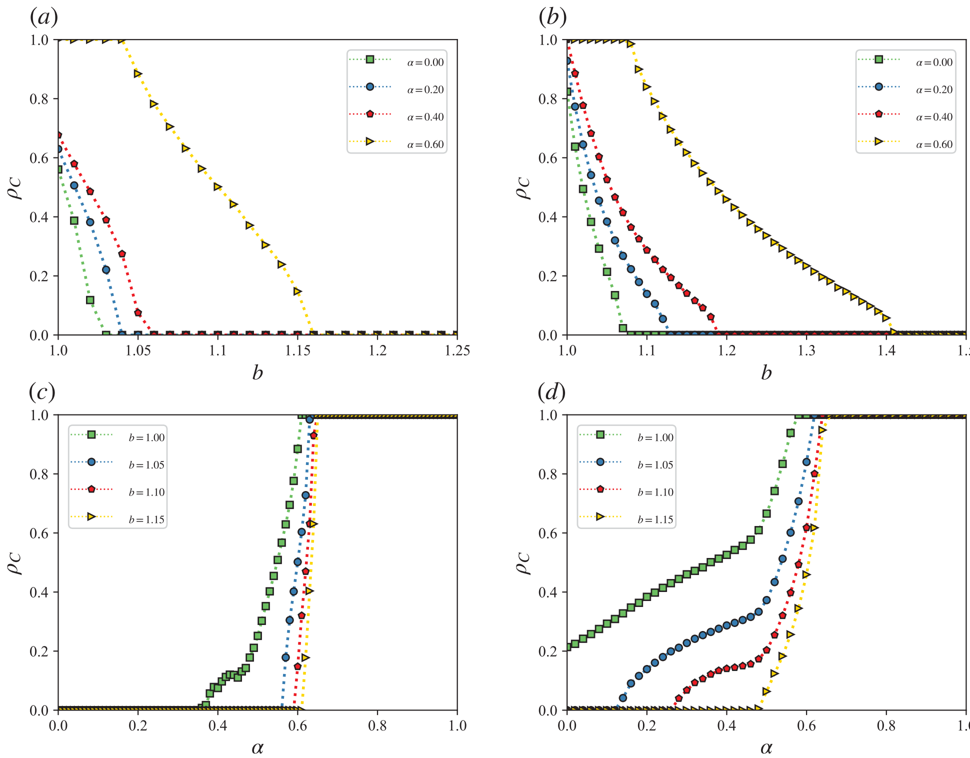

Fig. 1. (color online) Cooperation level ρ_C in the stable state versus b or α. (a–b) shows the results of cooperation level ρ_C versus b for $\alpha = 0$, $\alpha = 0.2$, $\alpha = 0.4$ and $\alpha = 0.6$ on regular lattice and small-world networks, respectively. (c–d) shows the results of cooperators level ρ_C versus α for $b = 1$, $\alpha = 1.05$, $\alpha = 1.1$ and $\alpha = 1.15$ on regular lattice and small-world networks, respectively. In the simulations, we set the population size N to 100×100, the rewiring probability $p = 0.1$ for Watts–Strogatz small-world network, and the noise level $K = 0.1$.

increase of the temptation to defect b for both regular lattice and small-world networks, as shown in Fig. 1(a) and Fig. 1(b), respectively. When the temptation to defect b reaches a critical point b_c, the cooperation level ρ_C decreases to zero continuously. The larger the parameter α is, the larger the critical point b_c is, indicating that higher values of α allow cooperation to persist even with a greater temptation to defect. In Fig. 1(c) and Fig. 1(d), we show how the cooperation level varies as a function of α for different values of b on regular lattice and small-world networks, respectively. These results confirm that the introduction of payoff-related inertia can significantly boost the cooperation level for a fixed value of b.

To gain further insights into the impacts of parameters α and b on the cooperation, we visualize the cooperation level ρ_C on the b-α plane for both regular lattice and small-world networks in Fig. 2(a) and Fig. 2(b), respectively. We observe that cooperation can be improved comprehensively for temptation to defect in the range $(1, 2]$. Additionally, the cooperation level of small-world networks consistently outperforms that of regular lattice networks for the same parameter settings. Moreover, the critical point b_c for cooperation extinction in small-world networks is always larger than that in regular lattice networks, indicating that cooperation can be sustained in small-world networks even in the presence of high temptation to defect. These findings further emphasize the role of small-world networks as promoters of cooperation when payoff-related inertia is considered. Furthermore, we found that when α is relatively large, such as $\alpha > 0.5$, the cooperation level ρ_C increases rapidly with the increase in α. For most values of temptation to defect b, it can even reach the state of full cooperation, i.e., $\rho_C = 1$. This phenomenon is observed in both square lattice and small-world networks.

To shed light on the mechanisms through which payoff-related inertia promotes cooperation, we present a series of snapshots illustrating the time evolution of strategy distributions in the system. The snapshots depict a fixed initial state where a cooperative cluster is surrounded by defectors, for different values of α, as shown in Fig. 3. In the early stages of the evolutionary process, cooperative clusters are rapidly invaded by defectors. This initial invasion leads to a significant reduction of cooperation, primarily driven by the higher payoffs that defectors receive at the borders of cooperative clusters. This payoff advantage allows defectors to proliferate and erode the cooperative structures. However, as time progresses, the impact of the parameter α becomes evident. For larger values of α, such as $\alpha = 0.4$ and $\alpha = 0.6$, cooperative clusters, which initially seemed vulnerable, begin to expand. This expansion is indicative of the increased stability and resilience of cooperators when payoff-related inertia is factored into the strategy-updating process. In stark contrast, when $\alpha = 0$, the cooperative clusters do not exhibit the same resilience. Instead, these clusters gradually shrink over time until they ultimately disappear, highlighting the critical role that payoff-related inertia plays in sustaining cooperation.

To better explain the role of the parameter α and individual payoffs in strategy updates, we reorganize the sum of individual inertia and payoff differences in the exponential part of Eq. (1). This yields:

$$\alpha I_i(t) + (1-\alpha)\Delta P = \alpha P_i(t-1) + (1-2\alpha)P_i(t) - (1-\alpha)P_j(t), \tag{2}$$

from which we can observe that when $\alpha < 0.5$, the current payoff and the payoff in previous step of player i hinder the strategy change, while the payoff of reference player j promotes the strategy change. However, when $\alpha > 0.5$, only the payoff from the previous step of player i hinders the strategy change, while both the current payoff of player i and the payoff of player j prevent the strategy change. In other words, when the parameter α crosses the threshold of 0.5, the influence of the current payoff on the evolution of the system shifts to the opposite effect. This explains why the cooperation level in the system shows a significant difference around $\alpha = 0.5$ when varying the parameter b.

In our model, individual inertia is payoff-related and dynamically influences the evolution of the system. We present the time series of cooperator density ρ_C, average inertia $\langle I_C \rangle$ of cooperators, and average inertia $\langle I_D \rangle$ of defectors from a random initial state for different values

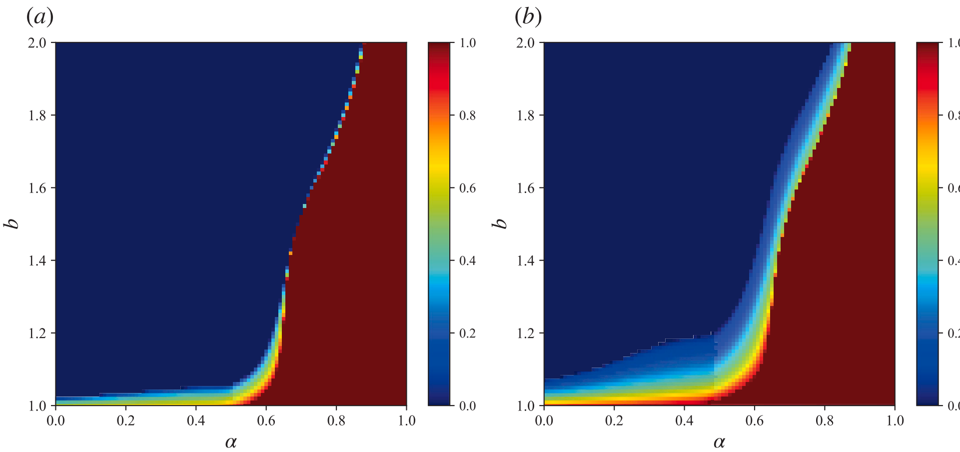

Fig. 2. (color online) Cooperation level ρ_C on a two-dimensional plane with $b \in (1,2]$ and $\alpha \in [0,1]$ for the two-dimensional square lattice (a) or small-world networks (b), respectively. In the simulations, we set the population size N to 100×100 and the rewiring probability $p = 0.1$ for Watts–Strogatz small-world network, where the noise level $K = 0.1$.

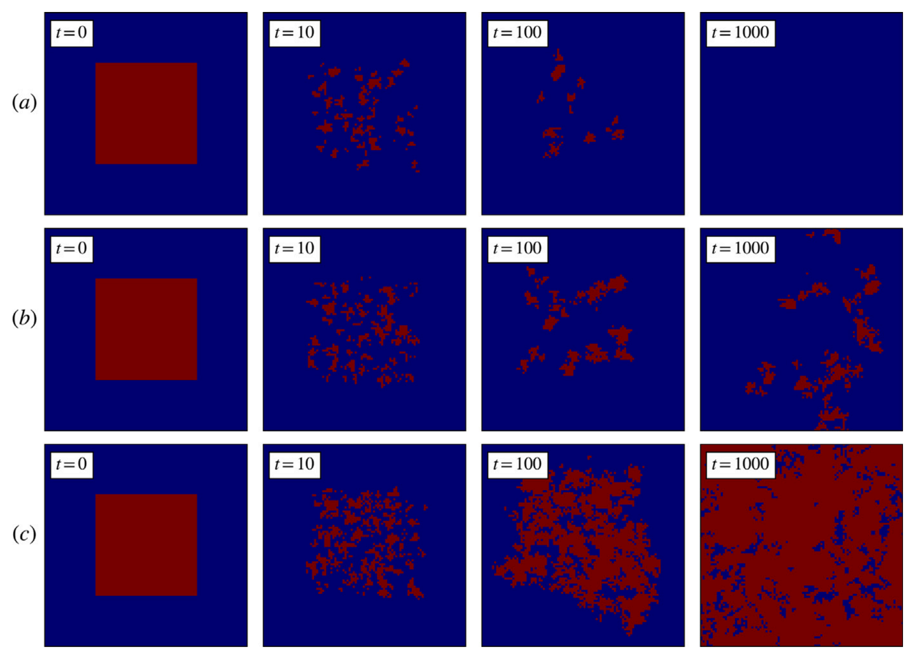

Fig. 3. Characteristic snapshots of C and D players on a 100×100 square lattice with a fixed initial state of a 50×50 cooperative clusters surrounded by defectors, where the noise level $K = 0.1$. Row (a) shows the results for $t = 0$, $t = 100$, $t = 1000$ and $t = 10000$ when $\alpha = 0.2$ and $b = 1.05$. Row (b) shows the results for $t = 0$, $t = 100$, $t = 1000$ and $t = 10000$ when $\alpha = 0.4$ and $b = 1.05$. Row (c) shows the results for $t = 0$, $t = 100$, $t = 1000$ and $t = 10000$ when $\alpha = 0.6$ and $b = 1.05$.

of α in Fig. 4. Although the quantitative results differ between regular lattices and small-world networks, the qualitative findings exhibit remarkable consistency. Initially, cooperators and defectors are evenly mixed, and the cooperative cluster is absent, resulting in defectors earning higher payoffs. Consequently, some cooperators quickly transition into defectors in the first evolutionary step, leading to increased average inertia. From Fig. 4(b)(c) or (e)(f), it can be observed that the average inertia of cooperators and defectors increase in the initial evolution. The increased inertia reduces the transition probabilities between cooperators and defectors, effectively preventing cooperators from collectively switching to defectors when defectors have a payoff advantage. This resistance to change allows some connected cooperators to survive the competitive pressure exerted by defectors, contributing to the initial formation of cooperative clusters. Subsequently, connected cooperators can gain higher payoffs through mutual cooperation, causing the cooperation level to rebound to a stable level with the formation and expansion of cooperative clusters. During this process, individuals at the boundaries of cooperative clusters may switch from cooperators to defectors or from defectors to cooperators. Due to differences in their inertia, the rates of these transitions may vary. Specifically, as cooperators change into defectors, their payoffs improve significantly by exploiting the nearest cooperators, leading to decreased inertia and motivating them to update their strategies. In contrast, when defectors change into cooperators, their payoffs may suffer losses, resulting in higher inertia for these cooperators, making their strategy less prone to change. From Fig. 4(b)(c) or (e)(f), it can be observed that the average inertia of cooperators is greater than that of defectors for large α. It should be noted that for larger values of α, such as $\alpha = 0.6$, the individuals in the system evolve to a steady state of full cooperation where is no change in the payoffs of all individuals, and thus the average inertia of both cooperators and defectors evolves to zero. In brief, payoff-related inertia slows down the evolution of system, preventing the rapid elimination of cooperators and allowing time for the formation of cooperative clusters in the early stages. Subsequently, it favors the transition of defectors into cooperators, contributing to the expansion and persistence of these cooperative clusters.

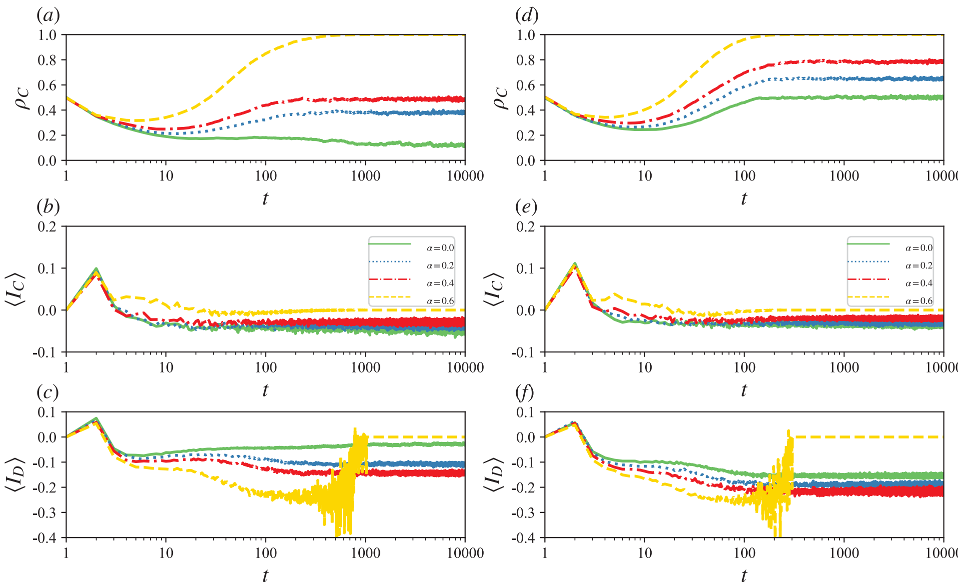

Fig. 4. (color online) (a–c) show the time evolution of ρ_C, average inertia of cooperators I_C, and average inertia of defectors I_D for different values of α on the regular lattice, respectively. (d–f) are the results for small-world networks. In the simulations, the temptation to defect b is 1.02, the noise level K is 0.1, and the population size N is 100 × 100. For Watts–Strogatz small-world network, the rewiring probability $p = 0.1$.

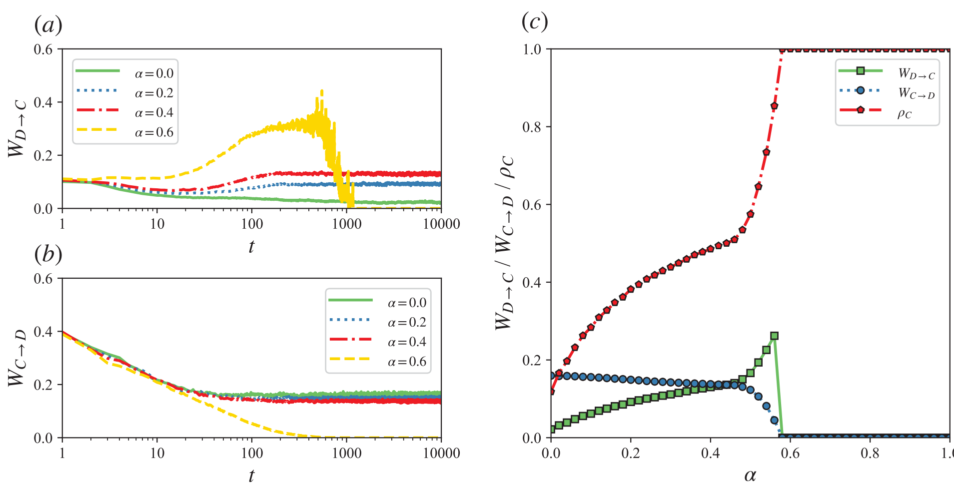

Fig. 5. (color online) The transition probability $W_{D\to C}$ of defectors to cooperators (a) and the transition probability $W_{C\to D}$ of cooperators to defectors (b) for different values of α on regular lattices. (c) The steady cooperation level ρ_C, transition probabilities $W_{C\to D}$ and $W_{D\to C}$ as functions of α. In all panels, the population size N is set to 100 × 100, the temptation to defect b is 1.02 and the noise level $K = 0.1$.

Given the significant impact of strategy-updating inertia on the dynamic transition between cooperators and defectors, we examine the transition probabilities $W_{D\to C}$ of defectors changing into cooperators and $W_{C\to D}$ of cooperators changing into defectors during evolution, as shown in Fig. 5(a) and Fig. 5(b), respectively. In the early stages of evolution, defectors have higher payoffs than cooperators, resulting in a higher probability $W_{C\to D}$ of cooperators switching to defectors and a lower probability $W_{D\to C}$ of defectors switching to cooperators. As cooperative clusters form, both transition probabilities stabilize. At this stage, individual inertia significantly impacts these probabilities. Specifically, the larger the parameter α, the greater the probability of defectors switching to cooperators, while the probability of cooperators switching to defectors decreases. For $\alpha = 0.6$, the system gradually evolves into a state of full cooperation, during which the probability of defectors turning into cooperators abruptly drops to zero. Fig. 5(c) illustrates the steady transition probabilities $W_{C\to D}$ and $W_{D\to C}$, along with the cooperation level ρ_C as functions of α. As α increases, strategy-updating inertia reduces the transition probability $W_{C\to D}$ from cooperators to defectors, increasing the transition probability $W_{D\to C}$ from defectors to cooperators. Consequently, higher values of α allow cooperators to sustain and expand during the later stages of system evolution. Fig. 6 shows the results for small-world networks, from which we can find the similar qualitative results.

4. Conclusion

In conclusion, this paper investigates the effects of payoff-related inertia on the networked evolutionary Prisoner's Dilemma game. We introduce individual inertia for strategy updating, determined by variations in total payoffs compared to the previous round. A parameter, α, is employed to control the impact of inertia on evolutionary dynamics. The results demonstrate that higher values of α consistently support more stable evolutionary cooperation, highlighting the positive influence of payoff-related inertia on maintaining cooperation.

In order to understand the underlying mechanisms that promote cooperation, we have carried out extensive simulations of the time

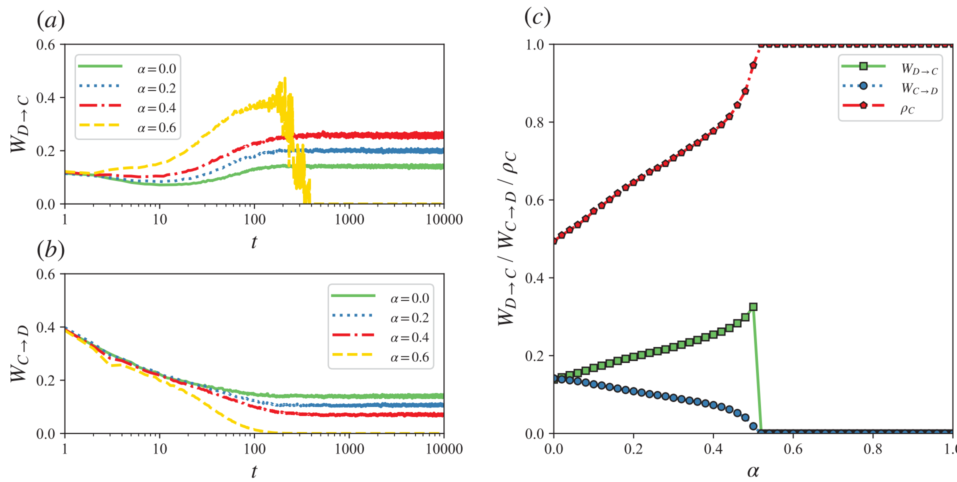

Fig. 6. (color online) The transition probability $W_{D\to C}$ of defectors to cooperators (a) and the transition probability $W_{C\to D}$ of cooperators to defectors (b) for different values of α on small-world networks. (c) The steady cooperation level ρ_C, transition probabilities $W_{C\to D}$ and $W_{D\to C}$ as functions of α. In all panels, the temptation to defect b is 1.02, the noise level $K = 0.1$, the population size N is 100×100 and the rewiring probability $p = 0.1$.

evolution of cooperator level, transition probabilities between C and D players, and snapshots of C and D players. We can find that the individual inertia of strategy updating is dynamic, and its impact on evolutionary cooperation also changes over time. At the early stage of evolution, the individual payoffs decrease significantly with the decrease of cooperator density, which increases the inertia of individuals and reduces the transition probabilities between cooperators and defectors. A lower transition probability between cooperators and defectors prevents cooperators from turning into defectors collectively, and some connected cooperators can rely on the formation of cooperative clusters to survive the competition with defectors. With the formation of cooperative clusters, the introduction of payoff-related inertia facilitates the transition of defectors to cooperators and promotes the expansion of cooperative clusters. In summary, payoff-related inertia slows down the evolution of the system, preventing rapid elimination of cooperators and allowing time for the formation of cooperative clusters at early stages. At the same time, it also facilitates the transition of defectors to cooperators, thus ultimately improving the level of cooperation. Furthermore, we have also applied our model on small-world networks, and we find that cooperation can be improved when the payoff-related inertia is introduced. Our results have thus shown that payoff-related inertia plays an important role in the emergence of cooperation in networked games of social dilemmas. At the same time, the cooperation level in small-world network is higher than that in regular lattice, which indicates that small-world network can also promote cooperation in the presence of payoff-related inertia.

In real economic activities, the behavior of individuals is often driven by interests. For selfish individuals, the initiative or inertia of individuals to choose the strategy is related to the interests brought by the strategies they have chose. Therefore, the proposed mechanism describes the characteristics of individual strategy-updating behavior to a certain extent. It is also expected that our work can provide some insights into understanding the emergence of cooperation, and at the same time it can provide some ideas for the regulation of cooperative behavior in a networked system.

CRediT authorship contribution statement

Chun-Xiao Jia: Writing – original draft, Methodology, Conceptualization. **Lin Ma:** Visualization, Validation, Conceptualization. **Run-Ran Liu:** Writing – review & editing, Validation, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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