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Memory-based spatial evolutionary prisoner's dilemma

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ABSTRACT

The promotion of cooperation provided by the network, compared to the well-mixed case, strongly depends on the type of strategy-updating mechanism. While many existing theoretical models have focused on agents memorizing neighbors' strategies, the specific use of memory in representing an individual's resistance to changing their own strategy – and its subsequent impact on the emergence of cooperation – remains underexplored. This study investigates the memory effect on the evolution of cooperation by integrating memory length and strength with the Fermi rule in the evolutionary prisoner's dilemma on a lattice. The Fermi rule incorporates both pairwise interactions and neighborhood interactions. Interestingly, we found the enduring period (END) and the expanding period (EXP) of cooperation, driven by network reciprocity. Notably, players with larger memory sizes exhibit a more pronounced manifestation of this phenomenon. Furthermore, our research highlights that a strong memory strength positively impacts the level of cooperation in the steady state. Additionally, if players prioritize the mean payoff difference among their neighbors over the pairwise difference with a randomly selected player from the neighborhood, it fosters a cooperative environment and enhances the overall level of cooperation. These findings underscore the vital role of memory and local interactions as crucial factors in shaping cooperation dynamics, offering valuable insights for future investigations in this rapidly evolving field.

1. Introduction

Since the inception of the idea introduced by Darwin as "survival of the fittest" [1,2], human beings have continuously pursued the development of advantageous traits. These acquired traits are frequently cultivated through rigorous competition, where individuals strive to gain a relative advantage by harnessing their inherent strengths, such as physical prowess, intellectual superiority, or proficient skills [3,4]. However, individuals also recognize that cooperation can yield greater benefits in the face of competition [5–7]. Through collaborative efforts, individuals can achieve resource-efficient allocation, exchange useful information, and share risks, thereby enhancing their competitiveness. As a result, cooperation has always been a central topic in various scientific disciplines, including physics [8,9], biology [10–12], sociology [13–15], economics [16–18]. Understanding the emergence and sustainability of cooperation is crucial for unraveling the intricate dynamics of social interactions and the evolution of complex systems.

Serving as a fundamental concept in game theory, the Prisoner's Dilemma Game (PDG) illustrates the inherent tension between individual rationality and collective cooperation [19,20]. Traditional game theory suggests that the rational strategy in the PDG is defection, as it maximizes individual gains regardless of the opponent's choice. However, empirical studies have shown that cooperation is prevalent in both natural systems and human societies, challenging the assumptions of conventional game theory. While defection is the rational choice in a one-shot PDG, cooperation can emerge and thrive through repeated interactions. In response to this social dilemma, evolutionary game theory provides a powerful framework for understanding the emergence of cooperation [21,22].

To highlight the prevalence of cooperation, researchers have proposed various mechanisms within the framework of complex networks [23]. One influential mechanism that has received significant attention is network reciprocity [24–27], where individuals interact with their neighbors in a structured population. The network structure plays a crucial role in shaping the emergence and sustainability of cooperation. Cooperation dynamics can vary considerably between well-mixed populations and structured populations, resulting in the formation of cooperative clusters or the maintenance of cooperation in specific network structures. However, real-world observations reveal variations in cooperation outcomes due to the inherent heterogeneity in social and biological interactions [28]. Building upon the seminal work

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by Nowak et al. on the PDG played on a spatial structure resembling a square lattice, subsequent researchers have conducted experiments on diverse network architectures, including random networks [29], scale-free networks [30], and small-world networks [31,32]. The ultimate objective has been to gain deeper insights into the complex interplay between network architectures and the emergence and sustainability of cooperation.

The strategy update rule, which resembles Darwinian selection or bounded rational learning, serves as the foundation of evolutionary game theory. There exists a wide range of strategy learning methods influenced by the local environment. In many cases, the better strategy choice for a given player relies on the payoff difference between their payoff and their neighbors' payoffs. The strategy learning process can vary in two key aspects: whom to learn from and the probability of learning [32]. Players can adopt the strategy from the neighbor with the highest payoff [28,33,34], or they can learn at random from their neighborhood [35–37]. The learning probability depends on the available information. When players only have access to previous round strategies, they tend to adopt better strategies like Win-Stay-Lose-Shift and Tit-For-Tat [38,39]. When both previous round strategies and resulting payoffs are available, the learning probability is determined by payoff comparison methods such as pairwise comparison [35,40].

Recent studies have started to focus on incorporating memory mechanisms into the strategy updating rules within evolutionary game models [41,42]. Memory can refer to players recalling their own previous strategies or the actions of opponents. The former represents individual learning, while the latter indicates social awareness [42]. One approach to incorporating memory is demonstrated by [43], who assume that each player not only remembers their own strategy but also the strategy of their interacting neighbor. This memory balance is crucial to forming reputation credibility. Another modification to the strategy updating rules is proposed by [44], who introduce accumulated payoffs as a factor in the modification of the Fermi function. Liu et al. set the probability of selecting a neighbor to be proportional to the number of unchanged strategies in past interactions [45]. Alonso et al. diminished accumulative payoffs in memory with a memory strength parameter [46]. In [47], players record the highest payoff strategies into their memories, leading to nonmonotonous behaviors influenced by memory size. Zhang et al. combined memory size and capacity, finding that in a dilemma snowdrift game, maintaining a memory of past interactions consistently boosts the level of cooperation [48].

In addition, several empirical studies have demonstrated that both the memory of players and the reputation of interacted players have a significant impact on the level of cooperation in evolutionary games. For instance, Bolton et al. suggested that in an evolutionary image-scoring game, the ability to remember the historical strategies of interacted players could positively influence cooperation [49]. Similarly, Cuesta et al. found that in an iterated Prisoner's Dilemma Game played among players connected on a dynamic network, remembering the last rounds of newly connected players can effectively promote cooperation [50]. However, it is worth noting that in a different context where an evolutionary PDG is played repeatedly twice in groups of six, cooperation tends to diminish over time [51]. These empirical studies collectively highlight the complex interplay between memory, reputation, and cooperation in evolutionary games.

To assess the impact of the memory effect and network reciprocity on strategy updating, we propose a spatial evolutionary Prisoner's Dilemma Game (PDG) model. This model uniquely integrates memory length and strength with the established Fermi rule, offering a fresh perspective on strategy updating in evolutionary games. Unlike previous studies where players often use memory to evaluate opponents' past strategies and reputation, our model limits players to their own memory, exploring the impact of self-memory on decision-making without the influence of others' historical strategies. This focus on self-memory represents a resistance to strategy change, diverging significantly from conventional models. This approach offers a nuanced understanding of how individual memory influences strategic evolution in the context of the PDG on a lattice network.

Specifically, within a square lattice of dimensions $L \times L$, each player is positioned to interact with their four adjacent neighbors. The population is initially balanced with equal proportions of cooperators and defectors. During each generation, players participate in a one-shot Prisoner's Dilemma Game (PDG) with their neighbors, accumulating total payoffs. Strategy updates hinge on the comparison of payoffs with a randomly chosen neighbor. The decision to adopt a new strategy is influenced by evaluating the payoff difference with the chosen neighbor, and by considering the average payoff among neighbors with the same and opposite strategies. To incorporate memory, we keep track of the last M strategies played by each player. This means that the more the current strategy has been used in the last M rounds, the less likely will be a strategy change, even in case the opposite strategy produced a higher payoff in the neighborhood. Additionally, it is important to note that memory can also decay, and the concept of memory strength α quantifies this decline.

2. Model

We investigate an evolutionary Prisoner's Dilemma Game (PDG) within a periodic boundary square lattice framework consisting of $N = L \times L$ players, denoted as $i \in \{1, 2, \ldots, N\}$. Thus, each player is connected to four neighboring players without edge limitation.

In each round of the PDG, each player i chooses a strategy s_i from the set $\{C, D\}$, representing cooperation (C) or defection (D), respectively. The payoffs are determined through pairwise encounters. If two cooperators meet, both receive a reward of R. On the other hand, if two defectors interact, both receive a punishment P. When a cooperator encounters a defector, the cooperator receives the minimal payoff S, while the defector receives the maximum payoff T. The payoff ranking follows the order $T > R > P > S$, and the condition $2R > T + S$ holds. In order to simplify the analysis, we establish the payoff values as follows: $R = 1$, $P = S = 0$, and $T = b \in (1, 2)$ [52]. This choice is made because there is only one remaining game parameter to control. It is noted that it is now not a pure PDG but a boundary game between PD game and chicken game [53]. Thus, the payoff matrix M for the game can be represented concisely as

$$M = \begin{pmatrix} R & S \\ T & P \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ b & 0 \end{pmatrix}. \tag{1}$$

Initially, each player is randomly assigned a strategy C or D with equal probability (i.e., 0.5 for both C and D). In other words, the initial distribution of cooperators and defectors is random across the lattice. At each time step $t = 1, 2, \ldots$, each player i plays the one-shot PDG with all 4 neighboring players simultaneously (see an example of $N = 2 \times 2$ players in Fig. 1(a)), and receives a sum payoff. Subsequently, each player i with strategy s_i undergoes social learning to acquire a better strategy from a randomly chosen neighbor j with strategy s_j simultaneously as well. Specifically, if $s_i = s_j$, player i retains its current strategy and does not learn anything. However, if player i and its neighbor j have different strategies, player i has the option to adopt the contradictory strategy s_j (i.e., $s_i \neq s_j$), with a certain probability as

$$P(s_i \to s_j) = \underbrace{\left(1 - \alpha \frac{M(s_i)}{M}\right)}_{\text{memory effect}} \underbrace{\frac{1}{1 + e^{-(\beta \Delta\pi + (1-\beta)\Delta\bar{\pi})/\kappa}}}_{\text{social influence}}, \tag{2}$$

The strategy transition probability takes into account the following two components:

Memory effect. Drawing inspiration from [54], we incorporate the memory length M and the memory strength $\alpha \in [0, 1]$ into the strategy updating mechanism. This is due to the fact that in a realistic scenario, individuals rely on their own memory for strategy updatings, rather than complete information about others' strategies. This assumption

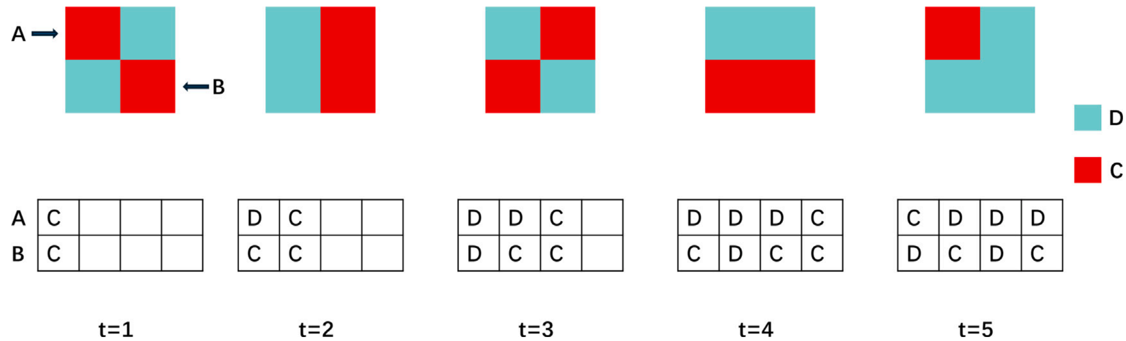

Fig. 1. The illustration of the memory storage in the evolutionary PDG process with memory size $M = 4$. Snapshots of $N = 2 \times 2$ players with cooperators and defectors.

aligns with real-world situations where individuals may not have full knowledge of others' past actions but are influenced by their own experiences. Here, the number of times player i had played strategy s_i out of the last M rounds is denoted as $M(s_i)$. Player i is more likely to retain its current strategy if the ratio $M(s_i)/M$ of the number of times it held the strategy s_i is higher. Furthermore, the aspect of memory decay can be quantitatively assessed through the parameter of memory strengthn α. When $\alpha = 0$ or 1, it presents an extreme example, implying that the individual will either completely forget the history or rely solely on the memory they have.

Social influence. Prior research always assumes that the more successful strategy will have a higher probability of being imitated by others [36,37,40,55]. However, the reference object for comparison can be different, e.g., it can be a randomly selected neighbor (pairwise comparison rule) [37,40], or the averaged local environment [35]. Here, we use the parameter $\beta \in [0, 1]$ to couple the pairwise influence $\Delta\pi$ and neighborhood influence $\Delta\overline{\pi}$, where $\Delta\pi = \pi(s_j) - \pi(s_i)$ denotes the payoff difference between player i and its neighbor j, and $\Delta\overline{\pi} = \overline{\pi}_{j\in\Omega_i}(s_j) - \overline{\pi}_{k\in\Omega_i\cup i}(s_k)$ denotes the mean payoff difference between the players with contradictory strategy and players with the same strategy with player i in the local neighborhood of player i (Ω_i). When $\beta = 0$ or 1, it presents an extreme example, implying that the individual will only imitate randomly selected neighbors or rely solely on the mean payoff difference among the whole neighborhood.

It is also noted that when $\alpha = 0, \beta = 1$, the strategy transition probability Eq. (2) reduces to the classic pairwise imitation rule. We will compare the joint impact of memory effect and social influence with the sole impact in Section 4.

In Eq. (2), κ represents the noise parameter that quantifies the uncertainty by strategy adoptions. Here, it is fixed at the traditional value of 0.1. We mainly focus on the fraction of cooperators in the population which can be calculated as

$$f_C(t) = \frac{N_C(t)}{N}, \quad t = \{0, 1, \dots, \infty\}, \tag{3}$$

where N_C signifies the number of cooperators among all players, and f_C represents the level of cooperation. Consequently, the range of f_C spans from 0 to 1, with 0 indicating the absence of cooperators and 1 representing an entire population of cooperators. The average cooperative levels in the stationary state required a sufficiently long relaxation time up to 2×10^4 Monte Carlo Step. To improve accuracy, the final results are averaged over 50 independent simulations.

3. Results

3.1. Memory size

At the initial time step $t = 0$, the population consists of an equal probability of cooperators (C) and defectors (D), resulting in a well-mixed distribution of strategies (see Fig. 2(a,g,m)).

We observe that the level of cooperation f_C has witnessed an initial decline over time regardless of the memory size M (as shown in Fig. 3(a)) with a moderate β ($\beta = 0.5$). However, as time progresses, an interesting pattern emerges where cooperators tend to form numerous small clusters. This phenomenon can be observed at the time step $t = 100$ in Fig. 2. Once the time step exceeds a certain value, cooperators start to erode defectors (e.g., the time step $t = 1000$ in Fig. 2). This can be also verified by Fig. 3(a). This is a well-known fact called the enduring (END) and expanding (EXP) periods in spatial games of cooperation [56,57]. Cooperators are initially weak and defeated by defectors. Thus, the fraction of cooperators decreases, but some small clusters still survive (END). If cooperators successfully survive in clusters, they can obtain higher payoffs based on mutual benefit within the region. Thus, cooperative clusters expand their size by absorbing defectors (EXP).

The memory size M plays a significant role in the spatial evolution of the cooperation with a moderate β. Specifically, a larger memory size M corresponds to a higher level of cooperation in the steady state. In other words, when players have a longer memory of past interactions, they are more likely to maintain a cooperator strategy, leading to a greater overall level of cooperation within the population.

3.2. Memory strength

Memory strength α has an effect on the evolution of cooperation over time, but not that much on the final level of cooperation (see Fig. 3(b)). Regarding the level of memory strength α, a higher value of α indicates greater resistance to strategy change within the memory. This means that players are less likely to switch strategies even when they face unfavorable payoffs. Consequently, during the initial prolonged period, where cooperation is expected to decline, a higher value of α contributes to a higher overall level of cooperation compared to lower values of α. As a result, for a higher value of α, it takes more time for cooperators to overcome the initial decline and start forming small clusters that erode defectors, which leads to an increase in cooperation over time.

3.3. Social influence

The controlling parameter β has a great impact on both the cooperation evolution process and the final level of cooperation. Lower weight β on pairwise interaction promotes a higher level of cooperation (as shown in Fig. 3(c)) since it allows players to focus on the collective behavior of their neighborhood rather than individual interactions. Specifically, when β is lower, players are more influenced by the mean payoff difference among players with the same strategy and contradictory strategies in their neighborhoods ($\Delta\overline{\pi}$) rather than the individual-level payoff difference ($\Delta\pi$). This means that players tend to imitate better strategies in their neighborhoods and adopt them. On the other hand, when the value of β exceeds a certain value, the level of cooperation (f_C) tends to decrease to approximately zero as time passes.

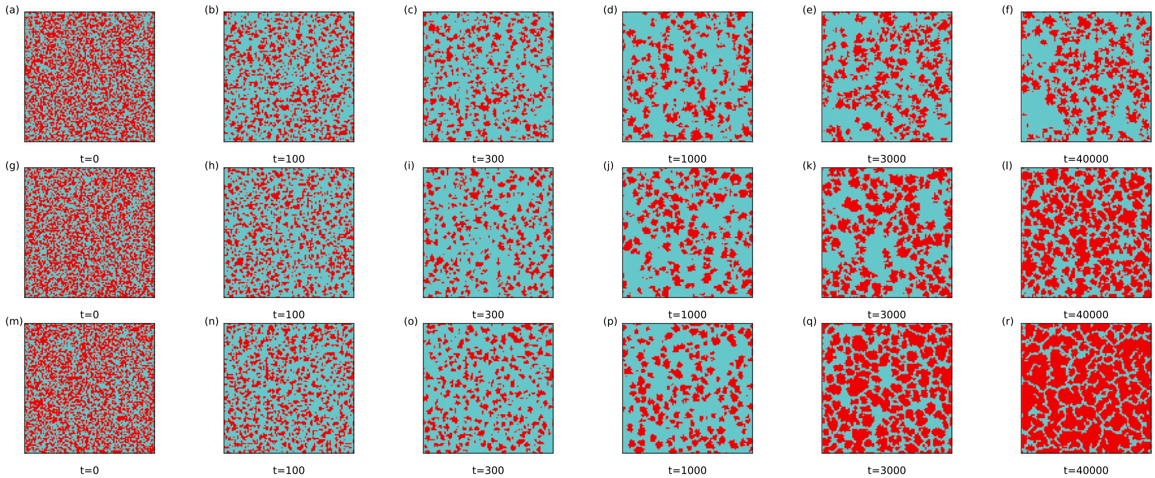

Fig. 2. Typical spatial distributions snapshots of cooperators (red) and defectors (blue) in a lattice. Settings: $N = 100 \times 100$, $\alpha = 0.9$, $\beta = 0.5$, and $b = 1.2$. The top, middle, and lower panels correspond to memory size $M = 5, 30, 100$, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

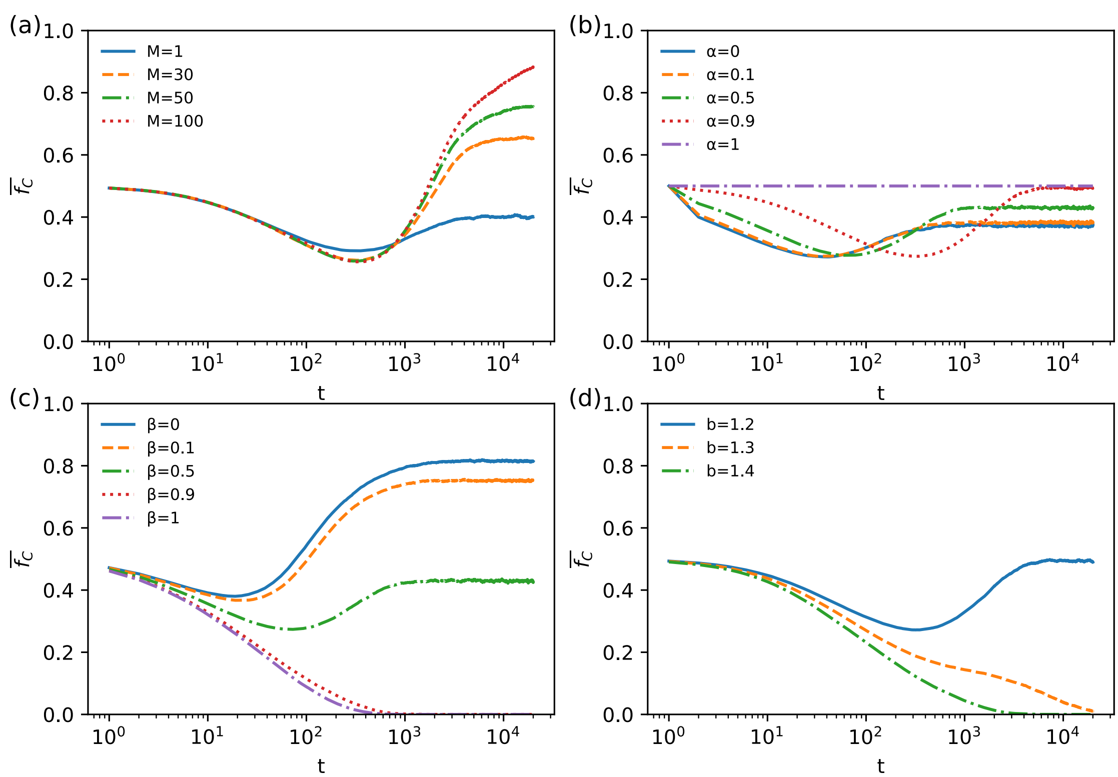

Fig. 3. The mean cooperation level $\overline{f_C}$ evolves over time t in a lattice with the total time $T = 2 \times 10^4$. Settings: (a) $\alpha = 0.9$, $\beta = 0.5$, $b = 1.2$; (b) $b = 1.2$, $M = 10$, $\beta = 0.5$; (c) $b = 1.2$, $M = 10$, $\alpha = 0.5$; (d) $\alpha = 0.9$, $\beta = 0.5$, and $M = 10$. Each data point is the mean of 50 independent simulations.

3.4. Parametric diagram

We comprehensively investigate the effects of all parameters on the final level of cooperation by examining parametric diagrams. These diagrams provide a visual representation of the parameter space and how different parameter values influence the level of cooperation.

Firstly, the payoff for a defector encountering a cooperator, i.e., b, has a significant impact on cooperation. Higher values of b can hinder cooperation (also shown in Fig. 3(d)). For instance, when b is large enough (e.g., $b = 1.4$), the region of complete cooperation (where $f_C = 1$) disappears from the parametric diagram (see Fig. 4(c,f,i)). This suggests that when the payoff for defection is significantly greater than the payoff for cooperation, defectors have a strong incentive to exploit cooperators, leading to a decrease in cooperation within the population. The absence of complete cooperation in the parametric diagram highlights the detrimental effect of high-defection payoffs on overall cooperation.

Secondly, the memory size parameter M plays a significant role in determining the final level of cooperation. Longer memory sizes tend to increase the level of cooperation. This can be observed in the parametric diagrams, where the purple regions (representing higher levels of cooperation) shrink or the red regions (representing the absence of cooperation) expand as the memory size increases (see Fig. 4(a,d,g)). The results suggest that a larger memory size with strong memory strength ($\alpha > 0.5$) makes cooperators resistant to change strategy even though defection can have more benefits. Due to the "unselfish"

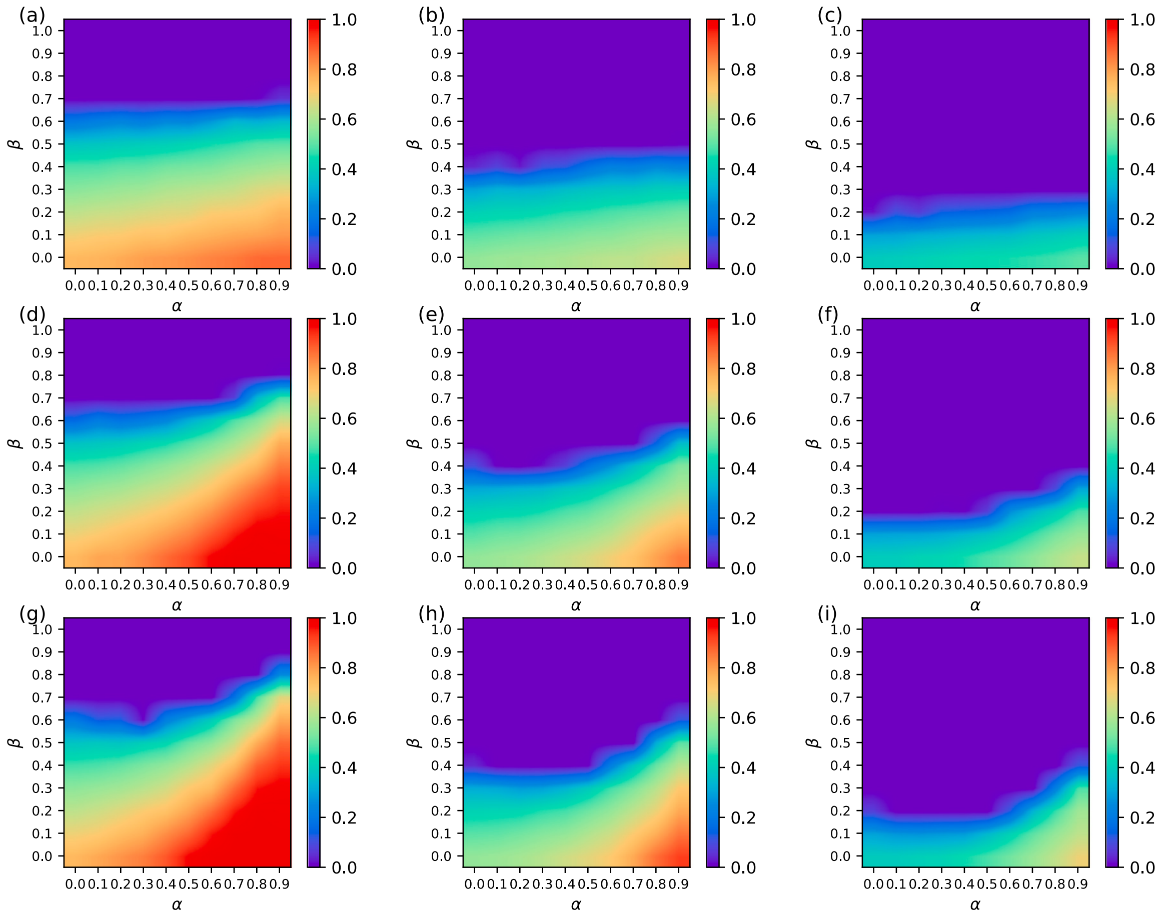

Fig. 4. The parametric diagram for memory strength α and controlling parameter β with settings: $T = 2 \times 10^4$. The three sets of panels represent varying memory sizes: $M = 10$ (top), $M = 50$ (middle), and $M = 100$ (bottom). Similarly, the panels from left to right showcase different b values: $b = 1.2$ (left), $b = 1.3$ (center), and $b = 1.4$ (right). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

behaviors led by the memory effect, cooperation can therefore survive and prevalent in the population.

4. Benchmark

4.1. The updating rule

Let us first discuss some special cases: (i) When the memory strength is $\alpha = 1$, the transition probability $P(s_i \to s_j)$ in Eq. (2) attains a constant value of 0 due to $M(s_i)/M = 1$. It implies that the mean level of cooperation remains as the initial level, i.e., $\overline{f_C} = 0.5$ in Fig. 3(b); (ii) When the memory strength is $\alpha = 0$, the strategy updating mechanism will reduce to the Fermi rule. Further, $\beta = 1$ and $\beta = 0$ correspond to the traditional Fermi rule with pairwise comparison and the modified Fermi rule with averaged local pairwise comparison, respectively. From Fig. 5, we can observe that as time evolves, the traditional Fermi rule (i.e., $\alpha = 0$ and $\beta = 1$) cannot promote cooperation but the modified Fermi rule (i.e., $\alpha = 0$ and $\beta = 0$) by considering mean payoffs in the neighborhood would. This result is in line with Ref. [35]; (iii) When the memory strength $\alpha \in (0, 1)$, $\beta = 0$ and $\beta = 1$ yields the combined effect of averaged local influence and memory or that of pairwise influence and memory. From Fig. 5 with setting $\alpha = 0.5$, we can observe that the memory effect indeed promotes cooperation compared with the case of without memory $\alpha = 0$.

4.2. An initial small cluster

The underlying reason for the sustainment and increase of the cooperation level f_C is primarily due to the formation of numerous small clusters of cooperators. To further investigate the role of these small clusters in facilitating the emergence of cooperation, we also consider a scenario where there exists an initial small cluster of cooperators.

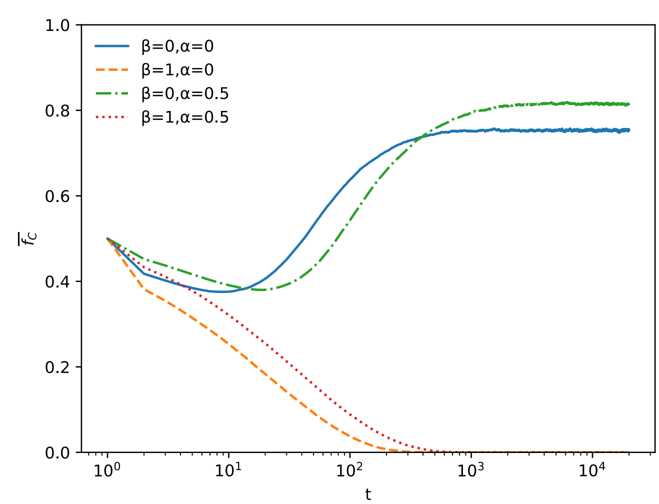

Fig. 5. The mean cooperation level $\overline{f_C}$ evolves over time t in a lattice with the total time $T = 2 \times 10^4$. Settings: $M = 10$ and $b = 1.2$. Each data point is the mean of 50 independent simulations.

Remarkably, regardless of the memory size M, the presence of an initial small cluster of cooperators with a size of 3×3 leads to

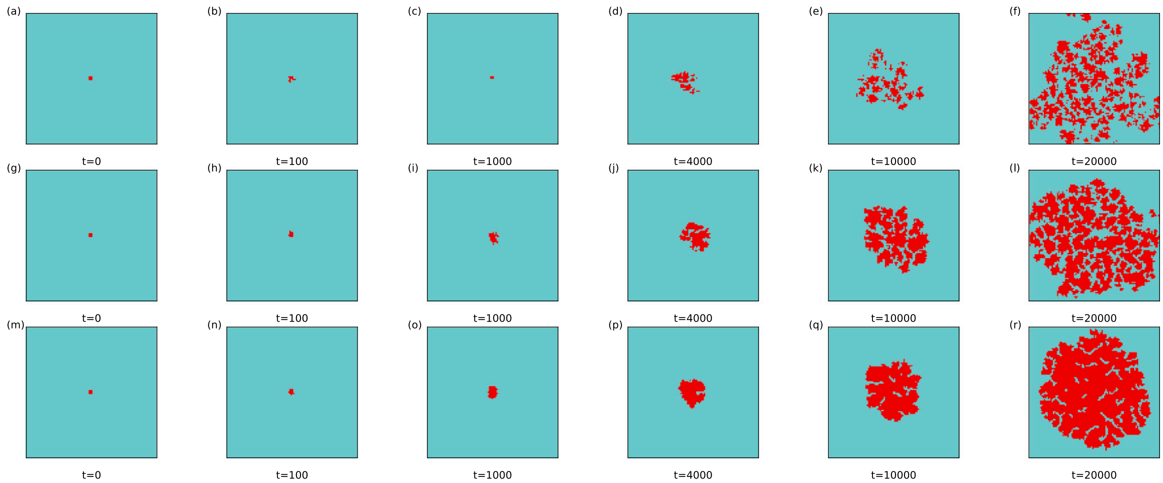

Fig. 6. Typical snapshots for spatial distributions of cooperators (red) and defectors (blue) initially from a 3 × 3 cluster of cooperators in the center of the lattice. The total number of players $N = 100 \times 100$, $\alpha = 0.9$, $\beta = 0.5$, $\kappa = 0.1$, and $b = 1.2$. The top, middle, and lower panels correspond to memory size $M = 1, 30, 100$, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

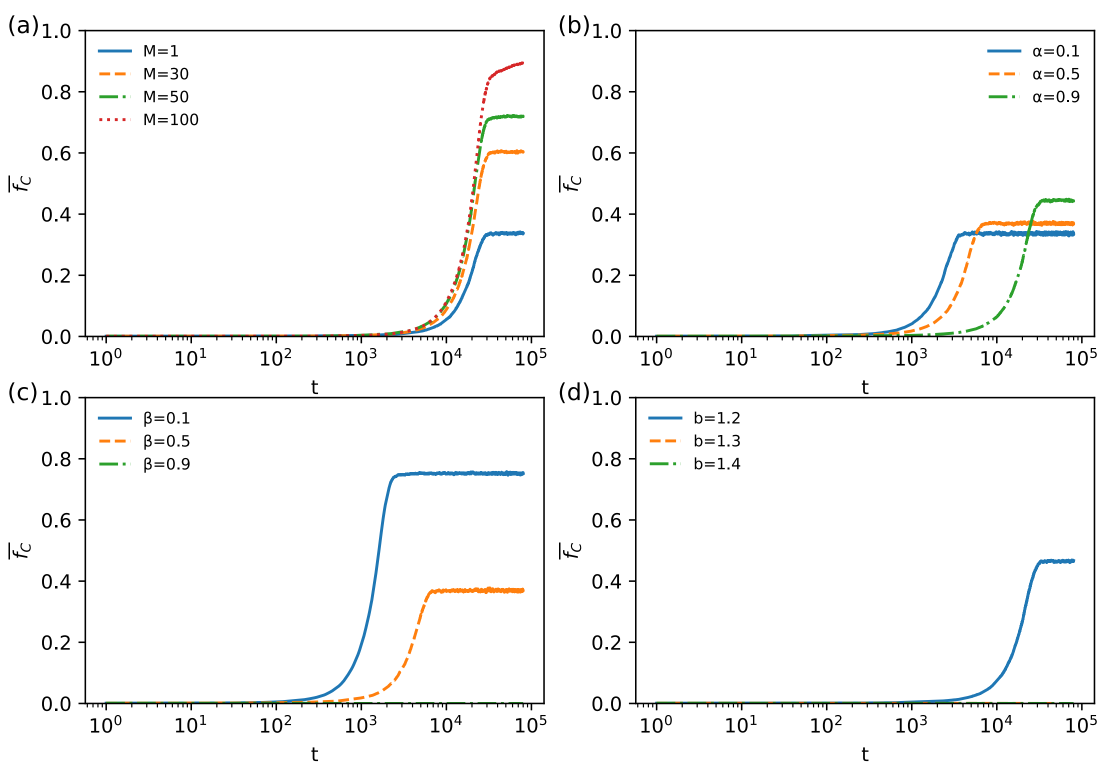

Fig. 7. The mean cooperation level $\overline{f_C}$ evolves over time t in a lattice with a total time $T = 8 \times 10^4$. It shows the case in which cooperators start from a 3 × 3 *small cluster*. Other settings in each panel are the same as Fig. 3.

the emergence of cooperation (see Fig. 6). This suggests that even a small group of cooperators can initiate cooperative behavior that spreads within the networked population. Notably, a larger memory size M contributes to a higher level of cooperation, similar to what we observed in the case of an equal distribution of two strategies.

What is particularly intriguing is that, under the same parameter settings, both the equal distribution case (shown in Fig. 3) and the small cluster case (shown in Fig. 7) result in nearly the same level of cooperation in the steady state. As long as the cooperation sustains, the system tends to converge toward a similar cooperative state in the long term regardless of the initial setting. This insight contributes to a deeper understanding of the factors influencing the emergence and sustainability of cooperation in complex systems.

4.3. Well-mixed population

Since cooperation can be promoted by network reciprocity [57], to determine whether cooperation can be promoted by the memory effect alone, without a spatial structure, we conducted the same evolutionary prisoner's dilemma game in a well-mixed population using the same settings. In each PDG round, each player randomly chose four other players to participate in the game. From Fig. 8, we can observe that cooperation could hardly emerge in a well-mixed population. The only exception is when the memory strength is $\alpha = 1$, the transition probability $P(s_i \rightarrow s_j)$ in Eq. (2) is a constant value of 0 due to $M(s_i)/M = 1$. Thus, the mean level of cooperation remains at the initial level, as shown in Fig. 8(b).

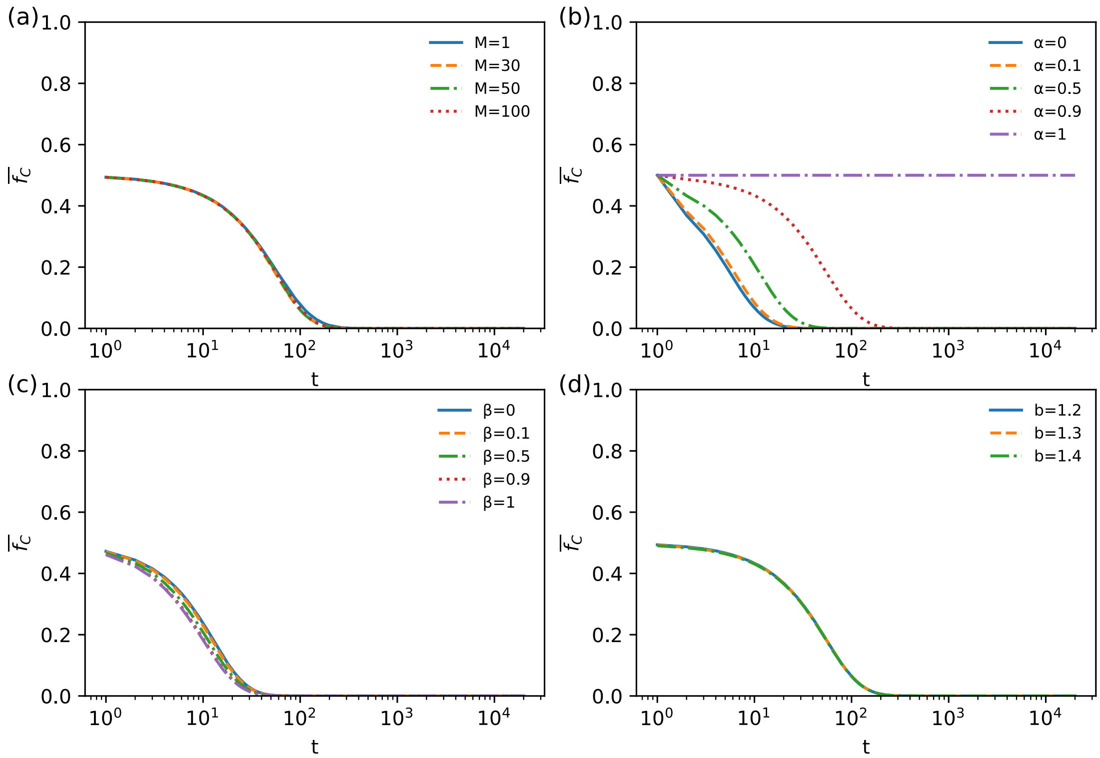

Fig. 8. The mean cooperation level $\overline{f_C}$ evolves over time t in a *well-mixed population* with total time $T = 2 \times 10^4$. Other settings in each panel are the same as Fig. 3.

5. Conclusion

In this work, we propose a memory-based strategy updating mechanism to study the evolutionary Prisoner's Dilemma Game (PDG) on a square lattice. The memory length and the memory strength of history rounds co-affect the given updating probability and further influence the emergence and sustainability of cooperation. In addition, we combined the pairwise comparison and mean payoff difference among neighborhoods to study the effect of pairwise influence and neighborhood influence.

Through simulation results, we have observed a pattern where the initial state experiences a decrease in cooperation due to uneven updating probabilities that favor defectors to exploit cooperators to maximize payoffs, and then increase as cooperators can sustain in small clusters based on network reciprocity. This phenomenon becomes particularly pronounced for players with longer memory sizes.

In addition, we have discovered that having a strong memory can lead to increased levels of cooperation in the long run. Furthermore, when players prioritize the mean payoff difference between neighborhoods over the difference between themselves and a random neighborhood player, it fosters a more cooperative atmosphere and boosts overall levels of cooperation.

The findings of this study align with previous research on evolutionary game theory [58], demonstrating that cooperation is fragile and easily disrupted by defectors [59,60]. The presence of defectors leads to a decrease in the overall cooperation level, highlighting the challenges faced by cooperative behavior in a competitive environment. However, it is important to note that the specific outcomes and trends observed in this study depend on the chosen parameter values and strategies. Different parameter combinations or alternative strategies may yield different results.

Further research could explore the effects of different parameter values, such as varying the balance between pairwise interactions and neighborhood influence or adjusting the resistance to strategic change. Additionally, investigating alternative strategies, such as conditional strategies [61] or adaptive strategies [62], could provide valuable insights into the dynamics of cooperation. For example, the direct reciprocity mechanism assumed in works [26,27] mentioned above in such that, after being exploited, a cooperator stops playing for some rounds with the defecting neighbor, which can be used to define conditional or adaptive strategies. Furthermore, extending the analysis to different network topologies or incorporating spatial heterogeneity could offer a more comprehensive understanding of cooperation in evolutionary games. Except for counting the number of cooperation or defection strategies in the last consecutive rounds M in the memory, several variants are possible, such as memories at different positions in the past could be differently weighted [46,63].

CRediT authorship contribution statement

Zhixiong Xu: Validation, Methodology. **Zhehang Xu:** Validation, Software. **Wei Zhang:** Writing – review & editing, Writing – original draft, Conceptualization. **Xiao-Pu Han:** Supervision, Methodology, Conceptualization. **Fanyuan Meng:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

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

Data will be made available on request.

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