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The confidence embodied in sticking to one's own strategy promotes cooperation

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ABSTRACT

Sticking to one's own strategy is typically a manifestation of confidence. In this paper, we assume that the player's confidence value increases when he gains in the game and decreases when he does the opposite. Become a confident player when the confidence value reaches the confidence threshold, and confident players have a greater preference for their strategy. The results show that the greater the variation of confidence value the more conducive to cooperation. When the temptation to defect is small, the larger the confidence threshold, the more conducive to cooperation, when the temptation to defect is larger, the smaller the confidence threshold, the more conducive to cooperation. The higher the degree to which confident players stick to their own strategy, the more conducive to cooperation, and the average confidence value of cooperators is significantly higher than that of defectors.

1. Introduction

Cooperation is a pervasive behavior in biological and social systems, but understanding the emergence and maintenance of cooperation among selfish individuals remains a challenge in the context of Darwinian evolution [1,2].

In recent years, evolutionary game theory as an effective research framework has been widely used in economics, biology, physics, mathematics and other fields [3–7]. Evolutionary game theory no longer models people as super-rational game parties, but achieves game equilibrium through continuous trial-and-error methods. There are many examples of exploring dilemmas, such as the prisoner's dilemma game (PDG) [8–10], the public goods game (PGG) [11], and the snowdrift game (SDG) [12]. In the PDG, although the total payoff is highest when you cooperate with each other, defection maximizes the payoff for the individual, which makes defection thrive in the population [13]. To address the dilemma, Nowak summarized five rules that facilitate the emergence of cooperation [14]: including kin selection, direct and indirect reciprocity, group selection and network reciprocity. Among these achievements, network reciprocity has been proved to be a effective way to promote the evolution of cooperation, which has attracted great interests to scholars from various disciplines. In 1992, Nowak and May creatively discovered that cooperators can resist the invasion of defectors by forming clusters on a square lattice [15]. Subsequently, many scholars have studied more complex networks, such as scale-free networks [16,17], small-world networks [18,19], random graphs [20,21], temporal networks [22] and so on. With the development of complex network research, the influence of population structure and data science on the evolution of cooperation in real society has been further studied, such as heterogeneous leadership structure [23], network segregation [24], asymmetric social interaction [25]. In addition, various mechanisms such as reward and punishment [26–28], aspiration [29,30], exposure [31], etc.have also been proposed and proved to be of great significance in promoting cooperation.

Coevolutionary rules can help one further understand the emergence of cooperation. In the rules of coevolutionry, not only will strategy evolve over time, but so will the environment, and there are many other factors that in turn affect the outcome of strategy evolution. Zimmermann M et al. proposed a coevolutionary dynamics model [32], which provides a realistic paradigm for the study of complex systems and has been widely studied [33–36]. Perc and Szolnoki summarized the coevolutionary rules [37], including dynamical interactions [38–40], population growth [41,42], the teaching ability of players [43,44], mobility of players [45,46], aging of players [47,48] and related factors [49–53]. In the teaching ability of players, many scholars believe that individuals with higher reputation or higher influence are more likely to transfer their strategies to others to learn [43,54]. However, another situation is easily overlooked, that is, individuals with certain charac-

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teristics (such as confidence) are more likely to be determined that their strategies are not affected by others.

Confidence is an important part of success, and overconfidence (believing you're doing better than you really are) can increase the likelihood of success and can also lead to false assessments or unrealistic aspirations [55]. How this "false" belief is stable in evolution and how it works has attracted scholars' research. Johnson and Fowler proposed an evolutionary model to study the evolution of overconfidence, and pointed out that overconfident populations are evolutionarily stable over a wide range of environments [56]. Li et al. investigated the effect of overconfidence and bluffing on cooperation in a resource competition game, where overconfidence increased the individual's self-perceived ability and bluffing increased the individual's demonstrated ability. Their research showed that bluffing can lead to the development of high level of overconfidence, and that overconfidence acts like a tool to overcome the negative effects of bluffing [57]. Li et al. also suggested that the both social norms and topological properties of interaction networks have substantial influence on the evolution of these "peer biases" [58]. Szolnoki and Chen showed that both underconfident and overconfident individuals facilitate the generation of cooperation in populations and that the presence of overconfident individuals enhances spatial reciprocity mechanisms [59]. He et al. considered the effect of confidence level on cooperation at static case and time-varied case respectively. Static heterogeneous confidence level can promote cooperation when parameters meet certain conditions, and cooperation level increase significantly when confidence level and strategy co-evolve [60]. The research method of confidence in the above literature is reflected by estimating one's own ability or payoff.

In reality, confidence can also be demonstrated by not easily changing one's strategy, characterized by the fact that successful experiences increase the confidence value, while failures decrease it, and that confident players have a greater preference for their strategy. For example, in an investment decision, if the trader is in profit then his confidence value will increase, while if the trader is in loss then his confidence value will decrease. A confident trader will have a lot of confidence in his investment strategy and will not change it easily, but an unconfident trader will imitate the trader who gets higher profits. The work in this paper takes an alternative perspective on confidence, studying the effect of co-evolution of confidence value and strategy on cooperation as confident players stick to their own strategy. Our results can provide new ideas for the study of confidence attributes and how to solve social dilemmas.

This paper is organized as follows. Section 2 provides the co-evolutionary model based on confidence value and strategy in detail. Section 3 presents and analyzes the evolution results. Finally, the main conclusions are given in Section 4.

2. Model

In the spatial PDG, all players are located on a $L \times L$ regular square lattice with a periodic boundary condition, and each player occupies a node and can play with its four nearest neighbors. There are two optional strategies, cooperation (C, $S_x = (1, 0)^T$) and defection (D, $S_x = (0, 1)^T$). For mutual cooperation, both players obtain the same reward R. For mutual defection, they are given the same punishment P. Otherwise, the player taking unilateral cooperation receives the sucker's payoff S, while the other adopting defection gets the temptation T. The payoff satisfies $T > P > R > S$ and $2R > T + S$. In order to simplify the parameters without losing generality, the weak PDG [15] is used in this paper, that is $R = 1, S = P = 0, T = b(1 < b \leq 2)$. The corresponding payoff matrix is:

$$M = \begin{pmatrix} 1 & 0 \\ b & 0 \end{pmatrix}. \tag{1}$$

Thus the payoff of player x when interacting with player y is $P_{xy} = S_x^T M S_y$. Player x obtains its total payoff F_x by interacting with all his four nearest neighbors, and the total payoff is calculated as:

$$F_x = \sum_{y \in G_x} P_{xy}, \tag{2}$$

where G_x is the set of neighbors of x.

2.1. Confidence value update rule

Let $CO_x(t)$ be the confidence value of player x at time t and $CO_x(t) \in [0, 2]$. The confidence value update rule of player x is defined as:

$$CO_x(t+1) = CO_x(t) + \Delta CO_x(t), \tag{3}$$

where $\Delta CO_x(t)$ is the average change of confidence value of player x after the game with four neighbors at time t. According to Ref. [61], the concept of average can be introduced to reveal the collective advantage of cooperation. In order to coordinate the relationship between neighbors, this paper averages the change of confidence value generated by the game between player x and all four neighbors, so we can get:

$$\Delta CO_x(t) = \frac{\sum_{y \in G_x} \Delta CO_{xy}(t)}{4}, \tag{4}$$

where $\Delta CO_{xy}(t)$ is the change of confidence value of player x after the game with his neighbor y at time t. According to our hypothesis, if player x gets a positive payoff in the game with his neighbor y, the confidence value increases, otherwise the confidence value decreases, so:

$$\Delta CO_{xy}(t) = \begin{cases} \delta, & P_{xy}(t) > 0, \\ -\delta, & P_{xy}(t) \leq 0, \end{cases} \tag{5}$$

where $\delta (\delta \geq 0)$ represents the variation of confidence value in a single game, and $P_{xy}(t)$ represents the payoff of player x in the game with its neighbor y at time t.

2.2. Strategy update rule

In the strategy update rule, a confident player decreases his likelihood of imitating his neighbor's strategy. Consider a probability that is influenced by both components, payoff and confidence value, and the probability that player x imitates one of his randomly chosen neighbor y at time t is given by:

$$P_{S_y \to S_x}(t) = \varepsilon_x * \frac{1}{1 + e^{\frac{F_x - F_y}{k}}}, \tag{6}$$

where the Fermi-function [7] on the right-hand side of the Eq. (6) is the part where the payoff plays a role. F_x and F_y represent the payoff of x and y, respectively. k represents the amplitude of noise. When not considering confidence value, $k \to 0$ means that the update is deterministic and happens only if F_y exceeds F_x, while $k \to +\infty$ means that player x imitates player y is completely random, and the population drifts in the neutral way. The ε_x on the left-hand side of the Eq. (6) is the part where the confidence value plays a role, and we define it as:

$$\varepsilon_x = \begin{cases} 1, & CO_x(t) < A, \\ \alpha, & CO_x(t) \geq A, \end{cases} \tag{7}$$

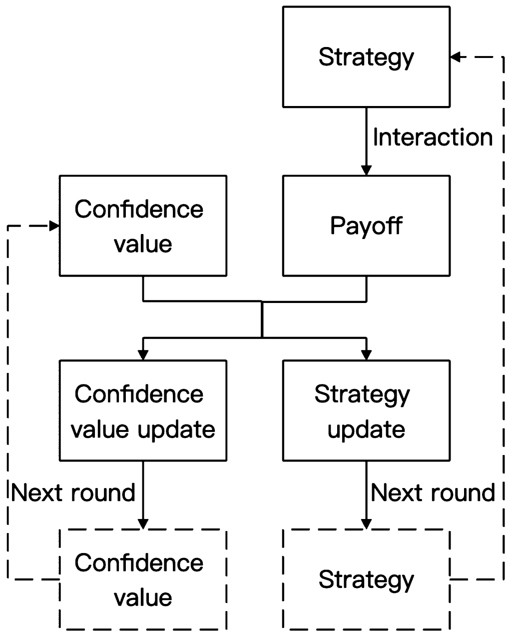


Fig. 1. The whole circulatory process of evolution. The solid arrow represents the evolution process of the current round, and the dotted arrow represents the process of the new confidence value and strategy in the next round. First determine the payoff (including one-shot game payoff and total payoff) based on the current round player 's strategy. Then the current confidence value and payoff jointly affect the confidence value update and strategy update, where the confidence value update rule refers to section 2.1 and the strategy update rule refers to section 2.2. The new confidence value and strategy generated after the confidence value update and strategy update are used as the starting conditions for the next round to continue the loop until the system reaches a steady state.

where A represents the confidence threshold, and if the confidence value of player x reaches A at the current moment, he is a confident player, and if it is less than A, he is an unconfident player. $\alpha(0 \leq \alpha \leq 1)$ indicates the degree to which confident players are willing to change their strategy, reflecting the irrationality of confident players compared to unconfident players. The smaller the α is, the less confident players are willing to learn each other 's strategy. When $\alpha = 1$, the confidence mechanism does not work. The rule of confident players and unconfident players' strategy update is the same. When $\alpha = 0$, confident players will completely keep their strategy unchanged.

At the initial moment all players have the same probability to choose cooperation and defection. We verified that for different distributions of players' confidence value at the initial moment, there is no effect on the qualitative nature of the results, and therefore set the confidence value of all players at the initial moment to 0.

For the same time step, all players perform strategy update and confidence value update synchronously, which ensures that all players will carry out both updates. We also performed simulations in the asynchronous [62] case, where the simulation results have no qualitative impact on the conclusions.

The whole circulatory process of evolution when given the distribution of initial confidence value and strategy is shown in Fig. 1.

3. Results

In this work, set $k = 0.1, L = 200$. We conduct the simulations on some large-scale networks (such as $L = 400$ or even larger) to eliminate the influence of the network size, and the qualitatively identical results can be obtained and omitted here. The simulation results are obtained by averaging over the last 2×10^3 time steps

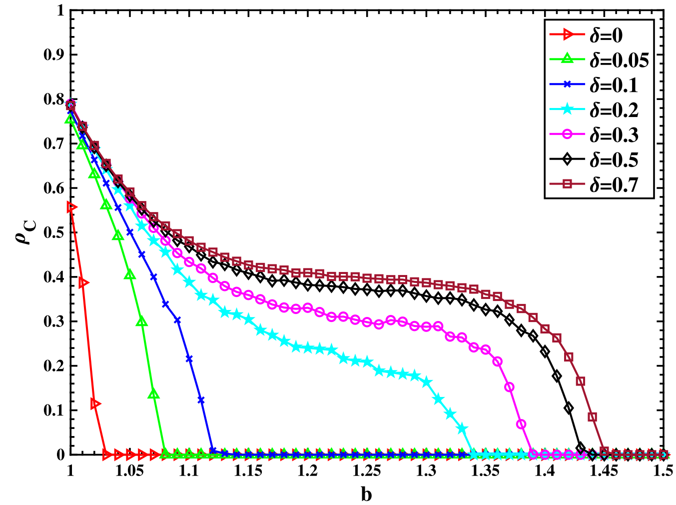


Fig. 2. The fraction of cooperation ρ_C versus the temptation to defect b when $\delta \in \{0, 0.05, 0.1, 0.2, 0.3, 0.5, 0.7\}$. The fixed parameters are $\alpha = 0.1, A = 1$.

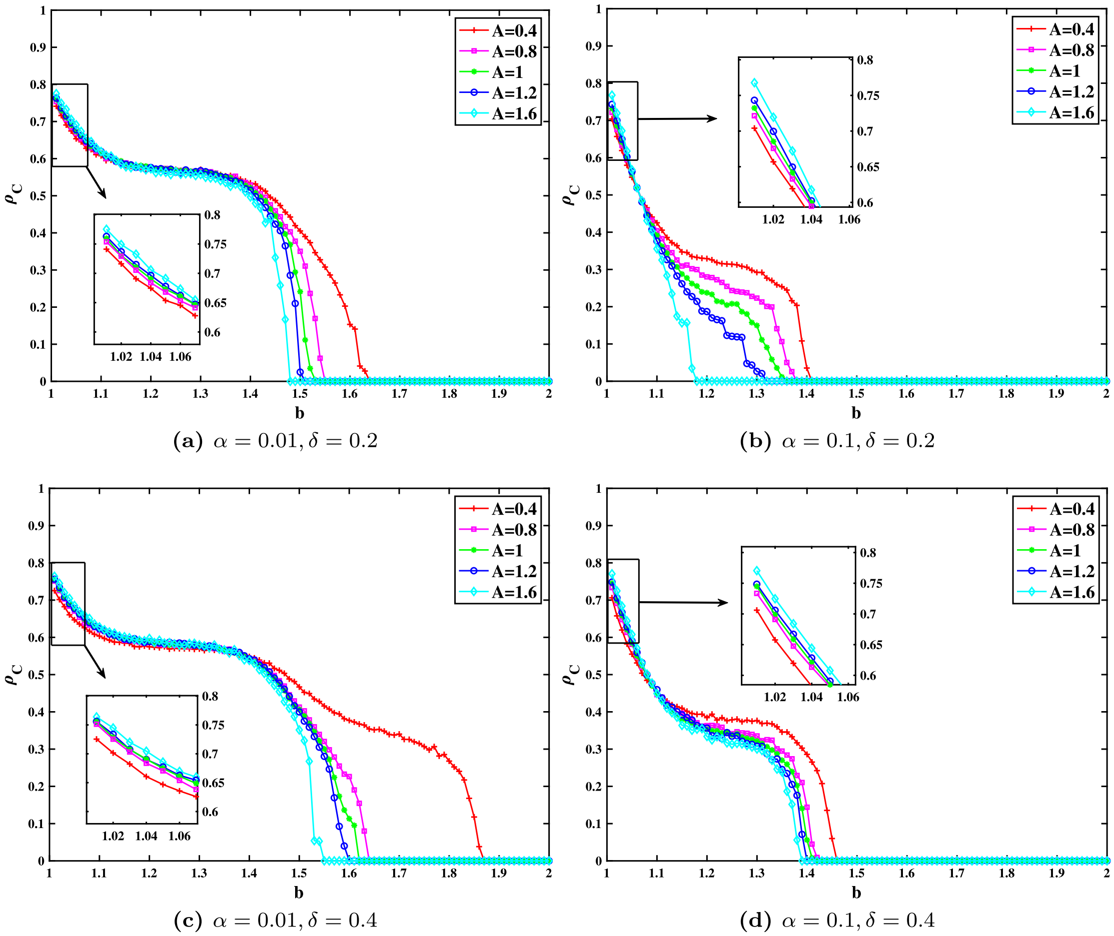
of the total 2×10^4, and the final results are averaged over 10 independent runs to guarantee the accuracy.

First of all, we consider the effect of different variation of confidence value on the evolutionary results. When $\alpha = 0.1, A = 1$, the evolutionary results of the fraction of cooperation ρ_C versus the temptation to defect b are shown in Fig. 2.

In Fig. 2, $\delta = 0$ indicates that all players have a stationary confidence value, and since all players are unconfident players at the initial moment, the model gives back the traditional model, with the fraction of cooperation decreasing to 0 at very small values of b. When $\delta > 0$, cooperation is promoted and the larger the δ the higher the fraction of cooperation and the greater the temptation to defect that can be resisted. However, it is worth noting that the promotion effect of increasing δ on cooperation at different b is not linear. When b is small, the promotion effect of increasing δ on cooperation is very limited. As b increases, the promotion effect of increasing δ on cooperation becomes more and more obvious. In addition, although the fraction of cooperation decreases as b increases, there are two trends in the change of the fraction of cooperation corresponding to different δ. When δ is small, it is approximately linear, but when δ increases to a certain value, it is nonlinear, and the fraction of cooperation decreases with a "buffer", i.e., the rate of decrease in the fraction of cooperation is smaller than the rate of increase in the value of b.

The confidence threshold determines how easy it is for a player to become a confident player. The smaller the confidence threshold, the more likely a player is to be a confident player, but the opposite is true when the confidence threshold is large. When $\alpha \in \{0.01, 0.1\}, \delta \in \{0.2, 0.4\}, A \in \{0.4, 0.8, 1, 1.2, 1.6\}$, the evolutionary results of the fraction of cooperation ρ_C versus the temptation to defect b are shown in Fig. 3.

As can be seen from Fig. 3, for different $\alpha - \delta$ combinations, the effects of different A on the fraction of cooperation are not significant when b is small. The inset shows that the fraction of cooperation is slightly higher when the value of A is large. When b is larger, the effects of different confidence threshold on the fraction of cooperation become significant, as reflected by the smaller the A the higher the fraction of cooperation and the greater the temptation of defect that the population can resist. The reason for the above phenomenon is because when the temptation to defect is small, the defectors have less advantage in terms of payoff, so the defectors invade the cooperators slowly to a small extent, and the cooperators can easily accumulate confidence value, so that different confidence threshold has little effect on the final fraction of co-



(a) $\alpha = 0.01, \delta = 0.2$ **(b)** $\alpha = 0.1, \delta = 0.2$

(c) $\alpha = 0.01, \delta = 0.4$ **(d)** $\alpha = 0.1, \delta = 0.4$

Fig. 3. The fraction of cooperation ρ_C versus the temptation to defect b when $A \in \{0.4, 0.8, 1, 1.2, 1.6\}$. The inset shows the details of the ρ_C corresponding to different A when b is small. The fixed parameters are (a) $\alpha = 0.01, \delta = 0.2$, (b) $\alpha = 0.1, \delta = 0.2$, (c) $\alpha = 0.01, \delta = 0.4$, (d) $\alpha = 0.1, \delta = 0.4$.

operation. However, when the temptation of defect becomes larger, the defectors' advantage in payoff becomes larger, so the defectors invade the cooperators faster to a greater extent. A smaller confidence threshold can ensure that the cooperators become confident quickly after forming clusters and thus can resist the invasion of defectors. But a larger confidence threshold will make some clusters of cooperators not yet formed confident and thus invaded by defectors, and thus the final fraction of cooperation will decrease. Therefore, the value of the confidence threshold has a greater effect on the fraction of cooperation when the temptation of defect is greater.

Furthermore, in order to more intuitively understand the phenomenon shown in Fig. 3, we fix $\delta = 0.2$, $\alpha = 0.01$, take $A = 0.4$ and $A = 1.6$, take $b = 1.05$ and $b = 1.45$, respectively. The fraction of cooperation as a function of time steps for different combinations of four A - b parameters, and the counts of the four categories (confident cooperator, unconfident cooperator, confident defector, and unconfident defector) under the four parameter combinations when the system is steady are shown in Fig. 4.

It can be seen from Fig. 4(a) that in the initial stage of the decline in the fraction of cooperation, the same b value has the same decline path, and the smaller b value decreases slowly. For different b value, the smaller A reaches the lowest point faster and the ρ_C of the lowest point is higher. When ρ_C reaches its lowest point, it starts to rise and eventually stabilizes as time evolves. The stable ρ_C under different A - b parameter combinations support the conclusion in Fig. 3. Comparing Fig. 4(b) and Fig. 4(c) we can see that when the temptation to defect is small, the difference between the four categories is mainly between the unconfident cooperators and the confident defectors. The larger the A value the higher the counts of unconfident cooperators and the lower the counts of confident defectors, while the difference between confident cooperators and unconfident defectors is not significant. Thus the larger the A value, the higher the fraction of cooperation. Comparing Fig. 4(d) and Fig. 4(e) we can see that when the temptation to defect is greater, the difference between the four categories is mainly between confident cooperators and unconfident defectors. The larger the A value the lower the counts of confident cooperators and the higher the counts of unconfident defectors. Although a larger A value also increases the counts of unconfident cooperators and decreases the counts of confident defectors, this change is negligible. Thus the larger the A value, the lower the fraction of cooperation.

The role of the confidence mechanism is reflected in the degree to which confident players stick to their strategy. When $\delta = 0.2$, $A = 1$, the heat map of the fraction of cooperation on the $\alpha - b$ parameter plane is shown in Fig. 5.

In Fig. 5, when $\alpha = 1$, the confidence mechanism will no longer work, and all players will update their strategy with only reference to their own and their chosen neighbor's payoff, at which point the model gives back the traditional model. When $\alpha < 1$, the confidence mechanism works and cooperation is promoted. The temptation of defect that cooperators can resist increases as α decreases, indicating that the higher the degree to which confident players stick to their own strategy the more cooperation is promoted. In addition, we also note that when α is relatively large, there is only a small degree of promotion to cooperation, but when α is relatively small, especially when α is less than 0.2,

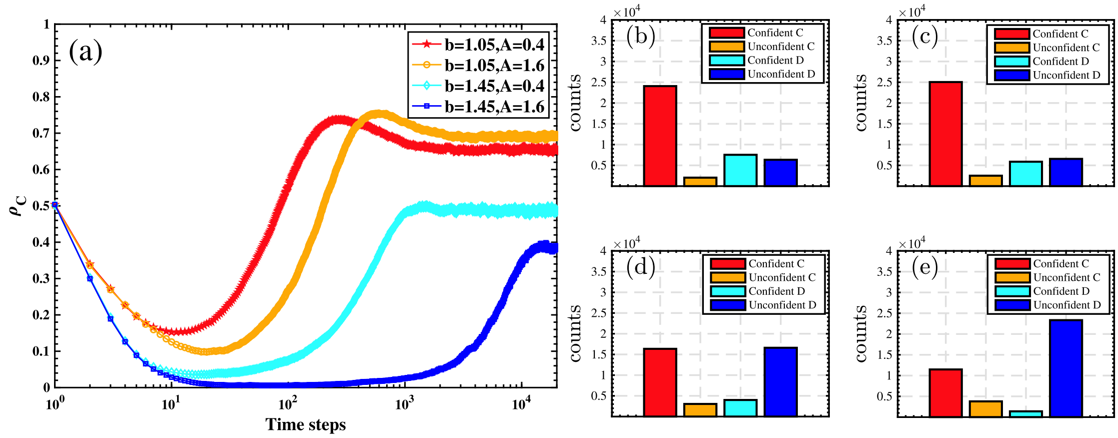


Fig. 4. The fraction of cooperation as a function of time steps for different combinations of four A - b parameters (a), and the counts of the four categories (confident cooperator, unconfident cooperator, confident defector, and unconfident defector) under the four parameter combinations, where (b) $b = 1.05$, $A = 0.4$, (c) $b = 1.05$, $A = 1.6$, (d) $b = 1.45$, $A = 0.4$, (e) $b = 1.45$, $A = 1.6$. The fixed parameters are $\delta = 0.2$, $\alpha = 0.01$. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

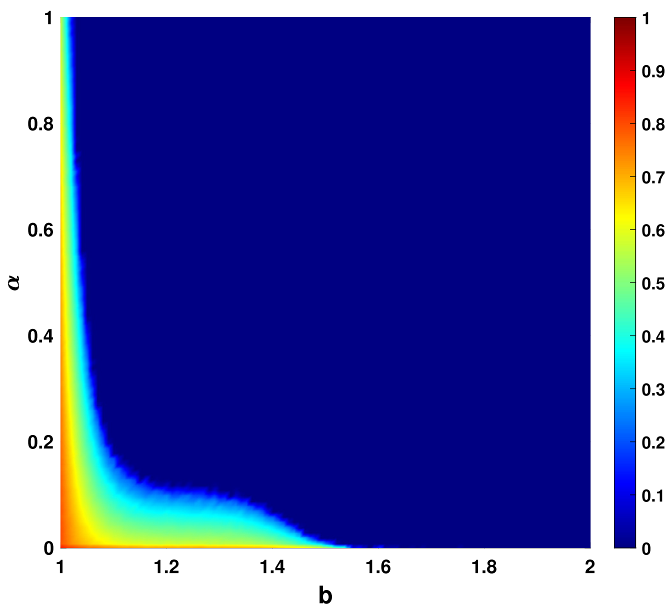


Fig. 5. Heat map of the fraction of cooperation ρ_C on the $\alpha - b$ parameter plane. The fixed parameters are $\delta = 0.2$, $A = 1$.

the promotion effect on cooperation is significant, suggesting that cooperators can survive greater temptation to defect when confident players stick to their own strategy to a high enough degree.

Next, according to Ref. [63], we performed a theoretical analysis of the stability of the equilibrium point. From the perspective of strategy transformation rate, define the average probability of a cooperator transforming into a defector as $P_{(C\to D)}$ and define the average probability of a defector transforming into a cooperator as $P_{(D\to C)}$, they can be expressed as:

$$\begin{cases} P_{C\to D} = \dfrac{\sum_{S_x=C} W_x}{A_C}, \\ P_{D\to C} = \dfrac{\sum_{S_x=D} W_x}{A_D}, \end{cases} \tag{8}$$

where W_x denotes the probability that player x imitates his neighbor and makes a strategy change, which can be obtained by Eq. (6). A_C and A_D denote the number of cooperators and defectors, respectively, which can be obtained by counting.

According to the stability condition of the equilibrium point, the system can be considered stable when the change rate of cooperators or defectors is 0. Let ρ_C denote the fraction of cooperation and $\Delta\rho_C$ denote the amount of change in the fraction of cooperation, then we can get: $\Delta\rho_C = (1-\rho_C)P_{D\to C} - \rho_C P_{C\to D} = 0$. Therefore, the fraction of cooperation in the stable state is:

$$\rho_C = \frac{P_{D\to C}}{P_{D\to C} + P_{C\to D}}. \tag{9}$$

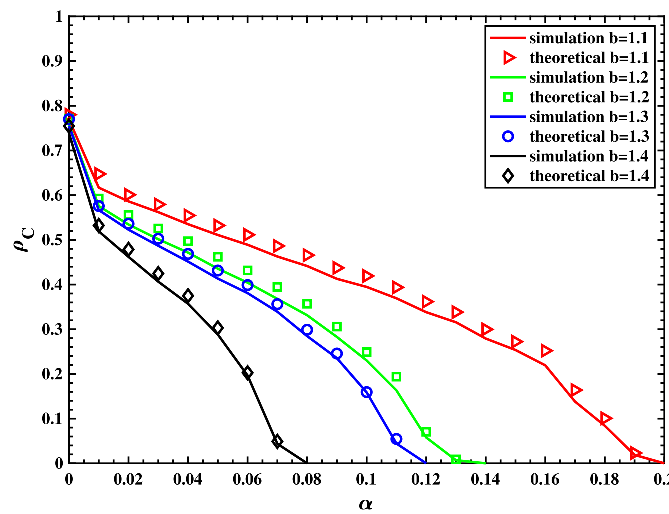


Fig. 6. The simulation and theoretical results of the fraction of cooperation ρ_C versus the degree to which confident players stick to their strategy α. The fixed parameters are $\delta = 0.2$, $A = 1$.

When $\delta = 0.2, A = 1, b \in \{1.1, 1.2, 1.3, 1.4\}$, the simulation and theoretical results of the fraction of cooperation ρ_C versus the degree to which confident players stick to their strategy α are shown in Fig. 6.

From Fig. 6, we can find that for different b, the fraction of cooperation in both simulation and theoretical cases basically coincides. As the α increases, the fraction of cooperation gradually decreases, and in addition, the smaller the value of b, the α corresponding to the disappearance of cooperators is becoming larger, which is consistent with the results in Fig. 5.

Furthermore, to explore the effect of different α on overall confidence value, the evolutionary results of the average confidence value of cooperators and defectors as a function of time steps when $b = 1.05, \delta = 0.1, A = 1, \alpha \in \{0.01, 0.1, 0.2\}$ are shown in Fig. 7.

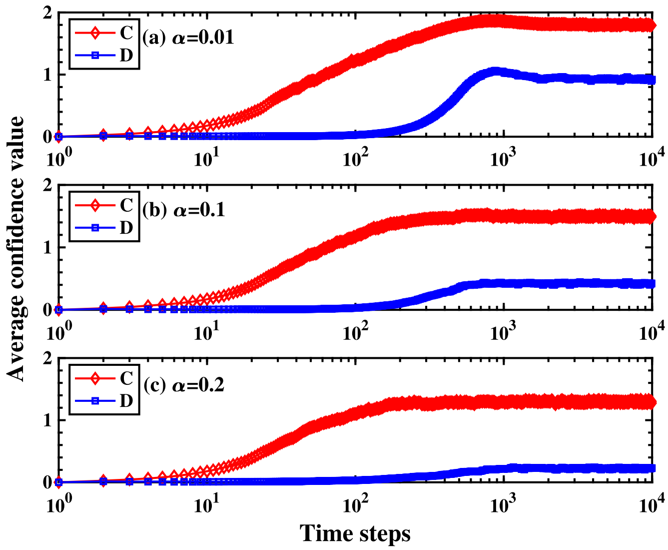


Fig. 7. The evolutionary results of the average confidence value of cooperators and defectors as a function of time steps for different α, where (a) $\alpha = 0.01$, (b) $\alpha = 0.1$, (c) $\alpha = 0.2$. The fixed parameters are $b = 1.05$, $\delta = 0.1$, $A = 1$.

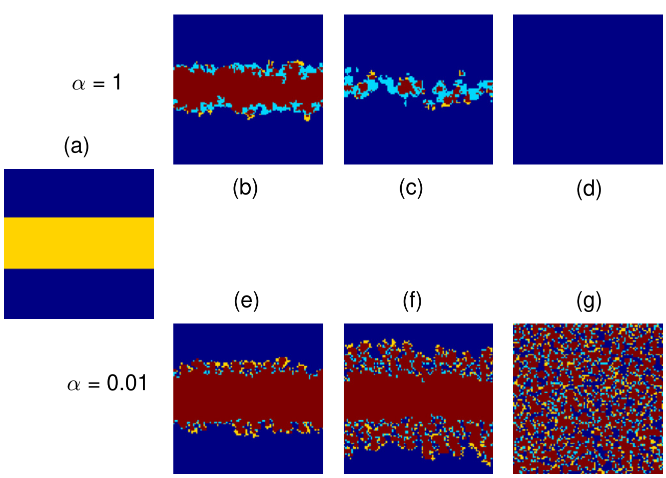


Fig. 8. Comparison of pattern formation for whether confidence mechanism works. The upper row $\alpha = 1$ indicates the evolutionary diagram with no effect of confidence mechanism (Panels (b) to (d)), and the lower row $\alpha = 0.01$ indicates the evolutionary diagram with the effect of confidence mechanism (Panels (e) to (g)). To facilitate the distinction, orange represents the unconfident cooperator, red represents the confident cooperator, blue represents the unconfident defector, and cyan represents the confident defector.

As seen in Fig. 7, the average confidence value of both cooperators and defectors tends to increase and then stabilize as time evolves. The average confidence value of cooperators is higher than that of defectors. An increase in α decreases the average confidence value of both cooperators and defectors, meaning that the more confident players stick to their strategy, the higher the overall confidence value will be. In addition, the effect of increasing α on defectors' average confidence value is greater than that on cooperators, with defectors' average confidence value only 0.22 when $\alpha = 0.2$, while cooperators' average confidence value is 1.27 at that time.

Finally, to further understand the effect of confidence mechanism on the evolution of cooperation, a set of snapshots of two different evolutionary paths starting from the same initial structure are shown in Fig. 8.

In Fig. 8(a), the two models start from the same initial structure, where unconfident cooperators are surrounded by unconfident defectors, which allows evolution to propagate along two domain walls, making it easier to reveal the characteristic movements of the propagation fronts [61]. There is a neutral drift between confident and unconfident cooperators or confident and unconfident defectors in the system, where their strategy does not change, but their own attributes change. Taking $\alpha = 1$ in the upper row of Fig. 8, there is no heterogeneity between confident and unconfident players at the time of strategy update, even though the players' confidence value is still changing at this point. In Fig. 8(b) we can see that the unconfident cooperators in the middle region drift into a cluster of confident cooperators by accumulating confidence, while the unconfident defectors accumulate confidence by invading the cluster of cooperators to form a large cluster of confident defectors. Since all players update their strategy exactly according to their payoff at this point, the gap in payoff makes the network reciprocity insufficient to support the presence of cooperators. In Fig. 8(c) the number of cooperators decreases gradually. As the number of cooperators decreases, the defectors are not consistently rewarded, and all of them become unconfident defectors in Fig. 8(d). In the lower row of Fig. 8, taking $\alpha = 0.01$, the confidence mechanism works. The cluster of confident cooperators becomes more solid because confident players are more willing to stick to their own strategy. In the Fig. 8(e) compared to the Fig. 8(b) did not cause a large invasion of confident defectors. Unconfident defectors located at the edge of the cooperators' clusters are absorbed as unconfident cooperators, as seen in Fig. 8(f), which extends the cooperators' clusters outward. As time evolves, in Fig. 8(g), the four categories coexist in the population.

In fact, the two evolutionary paths presented in Fig. 8 are exactly the two states in which the system can emerge. When other parameters are certain, if the degree to which confident players stick to their own strategy is not large enough, cooperators cannot exist, and only unconfident defectors exist in the system at this time. If the degree to which confident players stick to their own strategy is large enough, cooperation can emerge and be maintained, and the four categories of population coexist in the system at this time.

4. Conclusion

In this paper, we study the effect of the confidence embodied in sticking to one's own strategy on the evolution of cooperation in the spatial prisoner's dilemma game. The player's confidence value and strategy co-evolve. When the interaction achieves a positive payoff, the confidence value increases; otherwise, the confidence value decreases. A player is defined as confident when his confidence value reaches the confidence threshold, and the confident player has a greater preference for his own strategy.

Results show that the confidence mechanism can promote cooperation. The greater the variation of confidence value, the more it promotes cooperation, and the promotion effect of a larger variation of confidence value on the fraction of cooperation becomes more and more obvious as the temptation to defect increases. Confidence threshold indicates how easy it is for a player to become confident. When the temptation to defect is small, a larger confidence threshold is more favorable to cooperation, and when the temptation to defect is large, a smaller confidence threshold is more favorable to cooperation. In addition, the higher the degree to which confident players stick to their own strategy the more it promotes cooperation, and it has been verified from the perspective of theoretical analysis. For the average confidence value of cooperators and defectors, we find that the higher the degree to which confident players stick to their own strategy, the higher the overall confidence value.

Our work takes an alternative perspective on confidence, and there is still a lot of work to explore in the future. For example, our work only considers the game in the regular square lattice, and one of the future works is to explore the effect of the confidence mechanism in the heterogeneous network. In addition, our work adopts a uniform confidence threshold, and also the degree to which confident players stick to their own strategy is consistent, further study on the heterogeneity of these two parameters is worthwhile.

CRediT authorship contribution statement

Wenqiang Zhu: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Conceptualization. **Sha Song:** Writing – review & editing, Visualization, Supervision, Formal analysis, Conceptualization. **Yiwei Liu:** Formal analysis, Methodology, Software, Writing – review & editing. **Qiuhui Pan:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Mingfeng He:** Writing – review & editing, 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

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

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