



Coevolution of multi-game resolves social dilemma in network population

Chen Liu^{a,1}, Hao Guo^{b,1,*}, Zhibin Li^c, Xiaoyuan Gao^d, Shudong Li^{e,f,**}

^aCenter for Ecology and Environmental Sciences, Northwestern Polytechnical University, Xi'an 710072, China

^bSchool of Mechanical Engineering, Northwestern Polytechnical University, Xi'an 710072, China

^cSchool of Computer Science, Northwestern Polytechnical University, Xi'an 710072, China

^dTangnan Middle School, Xi'an 710072, China

^eCyberspace Institute of Advanced Technology, Guangzhou University, Guangzhou 510006, China

^fSchool of Computer Science, National University of Defense Technology, Changsha 410073, Hunan, China

ARTICLE INFO

Keywords:

Cooperation
Memory step
Snowdrift game
Prisoner's dilemma game
Coevolution

ABSTRACT

It is an open question to understand the emergence and maintenance of cooperation in nature and society. Aim to this issue, evolutionary game theory in networked population and its various derivations, like mixing game and multi-game, have proved an effective way to resolve the social dilemma. In this work, we propose the coevolution framework of strategy and multi-game: if a player, in prisoner's dilemma game, successively keeps its strategy constant for several times (referred as memory step), it will have opportunity to participate in snow drift game, which has lower dilemma strength than prisoner's dilemma game. Of particular, it is unveiled that for short memory step, the larger the value of sucker's payoff is, the higher frequency of cooperation will be. While for long memory step, middle sucker's payoff provides a best environment for cooperation. For all these findings, we also provide theoretical analysis, which guarantees further validation.

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1. Introduction

Cooperation is abundant in society, ranging from bacteria community to human being society. For example, parasites can overcome the defense of host through mutual cooperation, and human capture food together in primitive society. While all these observations seem to be inconsistent with the prediction of natural selection [1–3], in which cooperators should vanish because of high private cost. Thus, elucidating the emergence of cooperation among selfish individuals represents one of the most important challenges in social science and behavioral science, and has attracted great research interest. During the past decades, evolutionary game theory has become a powerful theoretical framework to investigate this puzzle [4–8]. In particular, prisoner's dilemma game (PDG) and snowdrift game (SDG) are two well-known models [9–13], where two players must choose cooperation or defection at the same time. They both receive the reward R for mutual cooperation, mutual defection will lead to the punishment P . If a cooperator plays with a defector, the former one receives a sucker's payoff S , while the other gets the temptation to defect T . In PDG, the payoffs strictly satisfy the ranking $T > R > P > S$

* Corresponding author.

** Corresponding author at: Cyberspace Institute of Advanced Technology, Guangzhou University, Guangzhou 510006, China.

E-mail addresses: ghFreezing@outlook.com (H. Guo), lishudong@gzhu.edu.cn (S. Li).

¹ These authors contributed equally.

and $2R > T+S$, which indicates that defection is always the best choice no matter what choice the opponent choose. While in SDG, the payoffs satisfy the ranking $T > R > S > P$, where the best option is to take the contrary action of your opponent (i.e., cooperation and defection consist the equilibrium state). Thus, compared with PDG, SDG shows lower dilemma strength [14].

In order to solve the social dilemma, a great number of mechanisms recently have been proposed in theoretical and experimental researches [9,15,16]. While Nowak attributed all these scenarios promoting cooperation to five key rules: kin selection, direct reciprocity, indirect reciprocity, group selection and spatial reciprocity [17–20]. Among them, spatial reciprocity has attracted great attention, because of its broad application in statistical physics and mathematics [21]. In network population, each player only interacts with its nearest neighbors, and thus cooperators can survive by forming compact clusters [19]. After this seminal idea, the study of evolutionary has been encapsulated into variety of network topologies, such as Boolean network [22], small-world network [23], scale-free network [24–27] and interdependent networks [28,29]. Besides, many different factors have also been proposed based on different networks to explore the influence of these factors on evolution of cooperation, such as reputation [30,31], punishment [32], migration [33–35], asymmetric [36] and aspiration [37], to name but a few. However, most majority of these mentioned works mainly focus on a simple game model, recent studies also investigate how cooperation survives in multigame or mixing game [38,39], which means that each player chooses the given strategies, yet adopts different payoff matrices.

In spite of great progress of recent years, there still exists one case receiving little attention: games that agents play is not strictly constant, they usually change according to the environment. Inspired by this fact, we here consider a coevolution framework of multigame: if the individual in PDG successively keep strategy constant for several times (referred as memory step), it can convert to SDG next step (for avoiding higher dilemma strength). However, once the individual who plays SDG changes its strategy, it will turn to play PDG next time.

The rest of this paper is organized as follows. In Section 2, we present our evolutionary game model. Section 3 gives a description of numerical simulation results. Finally, we discuss the results and conclude the paper in Section 4.

2. Model

We first consider the interaction network, where each player occupies the nodes of $L \times L$ square lattice with periodic boundary conditions. Each node is initially designed as a cooperator (S_x) or a defector (S_y) with equal probability, which can be described as:

$$S_x = (1, 0)^T, S_y = (0, 1)^T. \tag{1}$$

Besides, each player initially belongs to one of two populations (T_i) with the same probability. It is designed to play PDG once $T_i = 1$, and play SDG for $T_i = 2$. Following the previous literatures [8,14,23], we consider weak PDG and SDG, in which the rescaled parameter are defined as $R = 1, P = 0, T = b$, whereby $1 \leq b \leq 2$ ensures the proper payoff ranking, and $S = -\sigma$ ($0 \leq \sigma \leq 1$) corresponding to PDG, $S = \sigma$ corresponding to SDG. Thus, the payoff matrix can be expressed by matrix M_x .

$$M_1 = \begin{pmatrix} 1 & -\sigma \\ b & 0 \end{pmatrix}, M_2 = \begin{pmatrix} 1 & \sigma \\ b & 0 \end{pmatrix}. \tag{2}$$

At each time step, player i plays the game with its nearest four neighbors and obtains its payoff P_i

$$P_i = \sum_{j \in N_i} S_i^T M_{T_i} S_j, \tag{3}$$

where N_i represents the set of neighbors of individual i , M_{T_i} means the payoff matrix of player i . The neighbors' payoff can be obtained in the same way. The game is implemented using Monte Carlo (MC) simulations. At first, the random selected player i acquire its payoff according to Eq. (3); next, we choose one agent j randomly from player i 's four neighbors, who has payoff P_j ; last, player i adopts the strategy from neighbor j with the probability W depending on the payoff difference,

$$W(S_j \rightarrow S_i) = \frac{1}{1 + \exp[(P_i - P_j)/K]}, \tag{4}$$

where K denotes the noise of selection, including irrationality and errors [34]. Because the effect of noise K has been well studied in previous paper [40,41], we set K to 0.1. During one Monte Carlo step (MCS), each individual has a chance to update its strategy on average.

Subsequently, we will describe how different types of players change according to the following protocol. Before the game, player i has its own type T_i and strategy S_i . If player i with $T_i = 1$ successively keep its strategy unchanged in the subsequent M steps, which means that it invasion of opposite strategy, it will change to $T_i = 2$ and play SDG. While for $T_i = 2$, if player i fails to keep its strategy for one step, the value of T_i will change to 1, and it plays PDG next step.

Results of Monte Carlo simulations presented below were obtained on populations comprising 200×200 to 800×800 individuals, whereby the fraction of cooperators F_C was determined within last 5×10^3 full steps of overall 2×10^5 MCS. And the final results were averaged over 20–40 independent runs for each set of parameter values in order to assure suitable accuracy.

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