Applied Mathematics and Computation 320 (2018) 614–620

Contents lists available at ScienceDirect

Applied Mathematics and Computation

journal homepage: www.elsevier.com/locate/amc

Promotion of cooperation based on swarm intelligence in spatial public goods games

Ya-Shan Chen [a,b,c], Han-Xin Yang [c], Wen-Zhong Guo [b,d,e,*], Geng-Geng Liu [b]

[a] Zhicheng College of Fuzhou University, Fuzhou 350002, China
[b] College of Mathematics and Computer Science, Fuzhou University, Fuzhou 350116, China
[c] College of Physics and Information Engineering, Fuzhou University, Fuzhou 350116, China
[d] Fujian Provincial Key Laboratory of Network Computing and Intelligent Information Processing, Fuzhou 350116, China
[e] Key Laboratory of Spatial Data Mining & Information Sharing, Ministry of Education, Fuzhou 350003, China

ARTICLE INFO

PACS:
02.50.Le
89.75.Hc
64.60.ah

Keywords:
Swarm intelligence
Public goods games
Square lattice
Cooperation

ABSTRACT

In this paper, we introduce the swarm intelligence methods into the evolutionary dynamics, and have studied the impact of swarm intelligent algorithm on the evolution of cooperation among selfish individuals in the continuous version of spatial public goods games (PGG). We update an individual's strategy according to the memory which records the most successful individual strategy in the past (referred to as its personal best strategy) as well as the knowledge of the best current strategy found by its nearest neighbors (referred to as the neighborhood best strategy). Through extensive simulations, we find that the introduction of swarm intelligence into PGG can promote cooperation strongly. Other pertinent quantities such as the time evolution of cooperator density, the spatial distribution of strategies and the updated velocities are also investigated.

1. Introduction

Cooperative behavior is ubiquitous in both natural and social systems [1]. So far, the evolutionary game theory has provided a mathematical framework [2,3] to address the emergence of cooperation. The public goods game (PGG) [4] has long been established as a paradigm in studying cooperative behavior. The original PGG is established as an archetypical context that succinctly captures a conflict between group interest and individual interests [5,6]. In its simplest form, the game requires that players decide whether to contribute to a common pool or not. Regardless of the chosen strategy by the player himself, he receives an equal share of the public good which results from total contributions being multiplied by a fixed rate of return. Consequently, players are faced with the temptation of being free-riders and rational players invest nothing which causes the Tragedy of the Commons [7–9].

Considering the rapid development of complex network theory, much effort has been devoted to the evolutionary game on complex networks in the past decade [10–22]. To explain the emergence of cooperation, researchers have proposed many important mechanisms, such as the direct and indirect reciprocity [23–25], memory effects [26,27], noise [28–30], punishment and reward [31–35], migration [36–39], social diversity [40–43], volunteering [44–46], network reciprocity [47,48] and aspiration [49–53], for the recent reviews about the evolution of cooperation, we recommend the readers to refer tox [54–57] and references therein. Besides the above scenarios, the role of reputation mechanism is considered as an effective

* Corresponding author at: College of Mathematics and Computer Science, Fuzhou University, Fuzhou 350116, China.
E-mail address: fzugwz@163.com (W.-Z. Guo).

https://doi.org/10.1016/j.amc.2017.10.022
0096-3003/

approach to help the cooperators to form the cooperative clusters to resist the invasion of defectors [58–63]. Several typical examples include: Cuesta et al. [61] declared that the reputation really fosters the cooperation through experiments conducted within groups of humans playing an iterated prisoner's dilemma on a dynamical network. Wang et al. [62] presented a new reputation inferring mechanism to consider the difference of the inferring ability among agents, through simulations they found that the introduction of reputation inferring could promote the cooperation strongly. Chen et al. [63] proposed a model of public goods game with adaptive reputation assortment simultaneously taking the individual reputation and strategy transfer difference into account, and the results demonstrated that the cooperative behaviors can be drastically promoted after the reputation assortment is introduced. However, in the above mentioned works, only the individuals' past experiences are considered in the reputation mechanism. But in the complex real world systems, when individuals take strategies, they will not only be influenced by their past behaviors, but also consider the current environment. Inspired by the facts, here we propose a swarm intelligence method that take the historical behaviors and current environment into account. The swarm intelligence originates from the nature [64–68], swarm enables animals to solve problem that go beyond the capacity of single animal. Typical examples include termites swarm to build colonies, birds swarm to find food, bees swarm to reproduce. Essentially, the swarm intelligence is a mechanism that individuals interact with one another while learning from their own experience, and gradually move towards the goal. The swarm intelligence has been used in the prisoner's dilemma game and the experimental results show that the swarm intelligence promotes the cooperation [69–71].

What is more, in most of the previous studies, agents are assumed to choose only between the two discrete strategies, namely to either purely cooperate or to purely defect. However, in many realistic cases, people are unlikely to stick with one simple pure strategy. In this paper, we will use the continuous version of the public goods game [72,73]. A continuous variable from the unit interval [0,1] is introduced, which defines the fraction of the total cost a given player is willing to pay. The limits 0 and 1 recover the two pure strategies. It is important to study how players change their strategies, that is, increase or decrease their contributions to the common pool.

The following of this paper is organized as follows. In Section 2, we introduce the spatial public goods games model and the swarm intelligence. In Section 3, we show the experimental results and discussions. In Section 4, we summarize our findings.

2. Models and methods

Players are located on an $L \times L$ square lattice with periodic boundary conditions. Every player occupies a lattice point and has four neighboring points. During the evolutionary process, each player x participates in $k_x + 1$ PGG-groups centered at x and its k_x neighbors, where each group contains a central node and nodes connected to the central node. Initial, a strategy is randomly chosen for each player with uniform probability in the interval [0, 1]. At each time step, each player contributes a cost (i.e. the strategy s_x) in every group that it engages. The payoff of a player x associated with the group centered at a player y is given by

$$P_{x,y} = -s_x + \frac{r}{k_y + 1} \sum_{i=0}^{k_y} s_i, \tag{1}$$

where $r (r > 1)$ is an enhancement factor, $i = 0$ stands for y, s_i is the strategy of the neighbor i of y, and k_y is y's degree. The total payoff of player x is

$$P_x = \sum_{y \in \Omega_x} P_{x,y}, \tag{2}$$

where Ω_x denotes the community of neighbors of x and itself. After accumulating the payoffs in each game, all players synchronously update their strategies guided by swarm intelligence as follows.

Each individual has its own strategy, velocity, as well as a memory of the best strategy it has obtained so far. The strategy of each player is a continuous variable from 0 to 1, which determines the willingness to cooperate, and will be adaptive varied at each time step, that is, increase or decrease their contributions to the common pool. In this model, the velocity represents the amplitude of variation. For player i, its strategy s_i is changed according to

$$s_i(t+1) = s_i(t) + v_i(t+1), \tag{3}$$

and if $s_i(t+1) > 1$, then $s_i(t+1) = 1$, if $s_i(t+1) < 0$, then $s_i(t+1) = 0$. Each individual adjusts its velocity in a direction toward the most profitable strategy in its past actions and the best current strategy in the neighborhood, it is calculated using:

$$v_i(t+1) = w * v_i(t) + c_1 * [s_i(h) - s_i(t)] + c_2 * [s_{i^*}(t) - s_i(t)], \tag{4}$$

where $s_i(h)$ is the strategy that yields the highest payoff in all i's past actions and $s_{i^*}(t)$ is the strategy of i's neighbor with the highest payoff in i's neighborhood at time t. The velocity update equation includes cognitive c_1 and social c_2 acceleration constants, which determine the tendency of every individual to either adopt its own personal best available strategy or the current strategy of the most successful player within the neighborhood. Here c_1 and c_2 are two positive parameter and $c_1 + c_2 = 1$. The inertia weight w represents the previous velocity of the individual. In the spirit of Clerc's constriction factor