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Strategy Selection in Public Games with Punishment on Small World Network

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Abstract: **Investigation of punishment has shaken the positive role in the evolution of cooperation. However, punishment is ubiquitous in nature, and more favored by certain modern societies in particular. To explore the underlying principle of such phenomenon, we study the evolution of cooperation in the context of punishments subject to social network. The results suggest that punishment has a great effect on the evolution of cooperation. In the network structured population, highly cooperation emerged even with ordinary punishment. As the number of social neighborhood increase, the cooperation will decrease.**

Keywords: PSO (particle swarm optimization); ISD (Iterated Snowdrift dilemma); punishment; spatial structure

I. Introduction

Cooperation is a key force in evolution, exists in all scales of organization from unicellular organisms to complex modern human society [9, 27]. The emergence and stabilization of cooperative behavior has become a core problem in biology, economics, mathematics, computer science and sociology [20-22, 28]. Evolutionary game theory has proven to be one of the most fruitful approaches to investigate this problem, using evolutionary models based on so-called social dilemmas [29]. An enormous body of studies, however, have concentrated on the iterated snowdrift model (ISD) [7, 8], which was proposed by Axelrod in the early 1980s. Those works mainly focused on how to evolve cooperative behavior from a population of agents involved in this nonzero-sum game. Axelrod [20-23] applied evolution in order to determine whether it was possible to obtain successful strategies of mutual cooperation.

Early studies [33-36] of the ISD using the co-evolutionary approach consider only two choices, i.e., cooperation and defection for each player in the game. Over the years, various mechanisms have been proposed to help explain and understand cooperative phenomena. One of the possible mechanisms accounting for the promotion of cooperation is the consideration of spatial structure (reciprocity) [24]. The presence of structure [10-15] means that each individual does not interact with each other, but with a small subset of the population, which constitutes his/her neighborhood and is arranged according to an underlying network of relationships. This idea was very successfully introduced by Nowak and May in their seminal paper [30], they considered a spatial version of the 2*2 game and showed that spatial structure enables both cooperators and defectors to persist indefinitely (see [23,24] for a review).

Punishment is often considered as a different strategy from pure cooperation or pure defection [5,13,14]. In this paper, we do not consider moralists (or punishers) to have a different strategy than other players. Players can be cooperators, defectors, loners (or non-participators) and only the cooperators can punish the defectors. In this paper, we extend this line of research by studying the effects of spatial reciprocity on the evolution of cooperation in the *n*-choice iterated snowdrift (ISD) game. Agents in the population are mapped into social network for competition. At each time step, the focal agent participates in a game instance with other agents drawn from its local neighborhood. An agent's strategy, which is used to select an action, is defined by the number of choices and the payoff matrix. A bionic method, the PSO algorithm [26-29] with synchronous updating is used to evolve the strategies over time. In this paper, the behavior performances of players with different environmental factors in regular-connected network are first examined, such as the number of choices, the size of population et al. Comprehensive numerical simulations across a range of parameter settings by using PSO algorithm is to check whether cooperation can still be maintained in a regular-connected network, and the results are used for the comparison of the cases when the agents move in complex spatial structures. Secondly, the influence of the punishment is tested in this *n*-choice ISD game.

The rest of this paper is organized as follows. An overview of the core ISD problem and relevant historic related work is presented in Section II. A summary of the co-evolutionary model is given in Section III, along with a description of spatial structure used to evolve cooperation. Section IV explains the experimental procedure followed for this study, and the results are analyzed. Section V concludes this paper by summarizing some of the major experimental findings.

II. Background

In this section we explain the conventional social dilemma games, the ISD game model. In these two well-known nonzero-sum games, two isolated players repeat choose one of the two actions: cooperate and defect. The dilemma for the players is that they will eventually receive low payoff from mutual defection whereas higher payoff can be obtained from mutual cooperation. The conventional social dilemma games are the foundation of the research for cooperation in the following extended models.

A. Conventional Social Dilemma Games

In conventional social dilemma games, each player has two choices: cooperation and defection. A player would receive payoff as the payoff matrix set when his opponent makes his choice in games [1-6]. A reward (*R*) is given when both players choose to cooperate, whereas punishment (*P*) will be given if both of them choose to defect. In the situation where one player defects and the other player cooperates, the one who defects is awarded a tempting reward (*T*) but the one who cooperates will be given the sucker's punishment (*S*). Accordingly, the SD game relaxes some of these constraints by (1) allowing players to obtain some immediate benefits from their cooperative acts and (2) sharing the cost of cooperation between cooperators. Therefore, the SD game has $T>R>S>P$.

The Snowdrift game is a viable and biologically interesting alternative. It occurs whenever not only the recipient but also the cooperator draws some benefit from the act of cooperation [7-10]. For example, foraging yeast cells secrete an enzyme to lies their environment. The resulting food resource is vital for the survival of the cells, but it also represents a common resource that is prone to exploitation by cheaters avoiding the costly production of the enzyme. If a cell cannot exploit food resources provided by others it is better off producing the vital but costly enzyme despite the risk of being exploited by others.

Further information on the Snowdrift game is provided in a separate interactive tutorial on effects of population structures in the Prisoner's Dilemma as compared to the Snowdrift game. In addition, another tutorial on a variant, the Continuous Snowdrift game, is also available. The latter provides an intriguing theoretical explanation for the evolutionary origin of cooperators and defectors

Table 1. Payoff matrix of snowdrift dilemma game

A \ B	**Cooperate**	**Defect**
Cooperate	$b-c/2$	$b-c$
Defect	b	0

Table 1 illustrates the SD game in terms of costs and benefits to the players. A cooperative act results in a benefit b to the opposing player and a cost c to the cooperator, where $b>c>0$. Under this situation, if the opponent cooperates, a player gets the reward $R=(b-c/2)$ if he/she also cooperates, but can get $T=b$ by defecting. If the opponent defects, a player gets the payoff $S=b-c$ for being cooperative and $P=0$ for being defect. As the definition of SD game, the cooperation is a mixed evolutionarily stable equilibrium behaviour. To normalize the range of cost and benefit, we define $r_{SD} = c/(2b-c)$ as cost-to-benefit ratio.

B. Multiplayer Social Dilemma Games

In the *n*-player SD game, the payoff of a cooperator is dependent examined by Zheng et al. [20]. If there is only one cooperator in the group, the payoff is $b-c$. If two cooperators exist, then the payoff is $b - c/2$. With three cooperators, the payoff becomes $b - c/3$, and so on. On the other hand, if exists at least one cooperator, the free riding defector(s) will receive a payoff b without doing anything. However, if there is not any cooperator, the payoff is 0. Accordingly, the utility can be summarized as equation (1).

$$\prod n = \begin{cases} b - \frac{c}{i}, & for\ cooperators \\ b, & for\ defectors \quad when\ i > 0 \\ 0, & for\ defectors \quad when\ i = 0. \end{cases} \tag{1}$$

III. The Model

A. n-Player evolutionary social game with multi-level choices

There are two behavioral types, cooperators and defectors in previous models. Contributors incur a cost c to produce a total benefit b that is shared equally among group members. Defectors incur no costs and produce no benefits. Now add a third type, "Loners" or "Nonparticipant" (L), the members of which live on a small but fixed income σ. And the "punishers" (CP) , as the forth type, who not only contribute to the commonwealth of the group but also punish the defectors, reducing each defectors payoff by γ at a cost β.Combined with the previous type cooperator (C) and defector (D), four roles (added with two new types) construct a multi-level game model. The payoff matrix for the multi-level ISD game model shown in Table 2.

Table 2 is the payoff matrix of two players with multiple levels of choices, if more than two players in the group, the payoff matrix need to be adjusted to the equation in section II.

Table 2. Multi-level ISD Game Model

B \ A	**D**	**L**	**C**	**CP**
D	0	b	b	$b-\beta$
L	σ	σ	σ	σ
C	$b-c$	$b-c$	$b-c/2$	$b-c/2$
CP	$b-c-\gamma$	$b-c$	$b-c/2$	$b-c/2$

B. Network for interactions

For the cooperation in the industry-university-institute, social connections are important. Organizations or humans want to cooperate with someone who has close relationship and willing to cooperate. In spatial evolutionary environment, the players (or agents) of a population are distributed on a regular grid and interact with other players in its neighbourhood. In our model, the players are mapped to network nodes (vertices) and the edges (or links) which dictate the interaction topology. Each agent participates in an interactive game with other agent drawn from its local neighborhood. The regular-network is two-dimensional and agents are connected by the edges. The social network structure is considered in this section, and we define the distance *d* between agents as a measurement of the intimacy. All the individuals in the group are randomly distributed in a grid and the intimacy of them is also randomly defined based on the distance *d*.

A social network is a social structure made up of a set of social actors (such as individuals or organizations), sets of dyadic ties, and other social interactions between actors. The social network perspective provides a set of methods for analyzing the structure of whole social entities as well as a variety of theories explaining the patterns observed in these structures. The study of these structures uses social network analysis to identify local and global patterns, locate influential entities, and examine network dynamics.

A small-world network is a special type of social network [11-16] in which most nodes are not neighbours of one another, but most nodes can be reached from every other node by a small number of hops or steps. Specifically, a small-world network is defined to be a network where the typical distance L between two randomly chosen nodes (the number of steps required) grows proportionally to the logarithm of the number of nodes N in the network. The Watts–Strogatz model is a random graph generation model that produces graphs with small-world properties, including short average path lengths and high clustering. Figure 1 shows an example of small-world model by using Watts-Strogatz method. This method is also used in our paper.

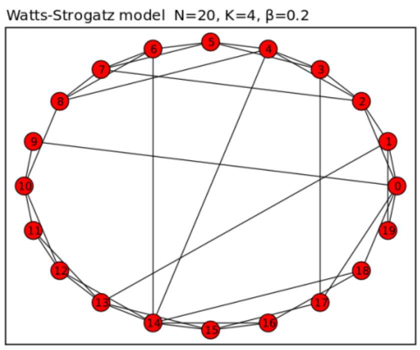

Figure 1. Example of small-world model.

C. Simulation of the model

Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality [17-20]. It solves a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

The PSO technique was introduced by Kennedy and Eberhart [26]. Inspired by the flocking behaviour of birds, PSO has been applied successfully to function the optimization, game learning, data clustering, and image analysis and neural networks training [24, 25]. PSO involves “flying” a swarm (or population) of *n*-dimensional particles, and through a problem space, each possible solution to the optimization problem need to search a single optimum or multiple optima [27-30]. Each particle has its own velocity, a memory of the best position it has obtained thus far (referred to as its personal best position), and knowledge of the best solution found by other particles (referred to as the global best solution).

In the PSO algorithm, each particle adjusts its position in a direction toward its own personal best position in a direction toward its own personal best position and the global best position.

In general, the neighborhood best position is calculated as

$$P_{gd}^{k+1} \in \{NE_i | f(P_{gd}^k) = \max\{f(x), \forall x \in NE_i\}\} \quad (2)$$

with the neighbourhood defined as

$$NE_i = \{P_{gd}^k\left(i - \frac{l}{2}\right), \ldots, P_{gd}^k(i-1), P_{gd}^k(i), P_{gd}^k(i+1), \ldots, P_{gd}^k\left(i + \frac{l}{2}\right)\} \quad (3)$$

The velocity of the particle is calculated using:

$$V_{id}^{k+1} = \omega V_{id}^k + c_1 rand(0,1)(P_{id}^k - X_{id}^k) + c_2 rand(0,1)(P_{gd}^k - X_{id}^k)$$

(4)

We simulate the model by the following procedure shown in Figure 2:

Let
N be the number of players in a *Snowdrift Game;*
L be the number of levels in a payoff matrix;
PNum be the size of particle swarm;
S be the spatial structure of the ISD Game;
k and K be the current generation and maximum number of iterations, respectively;
x_{id}^{k} and v_{id}^{k} be the position and velocity of the ith particle at iteration k on the specific d-dimension, respectively;
$v_{si\max}^{d}$ be the dth dimensional maximum velocity of ith particle and its neighborhoods;
fitness(i) be the fitness function of the ith particle;
p_{sigd}^{k} be the dth dimensional global best position of the ith particle and its neighborhoods ;
p_{id}^{k} be the dth dimensional history best position of the ith particle so far during k iteration;
Step 1(Initialization): For each particle i and dimension d
Step 1.1: Initialize *N, L, PNum, K*. .
Step 1.2: Initialize x_{id}^{k} with an integer between -1 and 1 according to the payoff matrix randomly.
Step 1.3: Initialize v_{id}^{k} with a real number between $-v_{si\max}^{d}$ and $v_{si\max}^{d}$ randomly.
Step 1.4: Calculate *fitness(i)*.
Step1.5: Initialize p_{id}^{k} with a copy of x_{id}^{k} .
Step 1.6: Initialize p_{sigd}^{k} with the best p_{id}^{k} among the *PNum* particles.
Step 2: Repeat until $k>K$.
Step 2.1: Determine *N, L, PNum* of the game.
Step 2.2: Random choose N players and for each player in the game do
Step 2.2.1: Compare performance against current personal best position, if need to update then use Eq.(9).
Step 2.2.2: Compare performance against neighborhoods' best position, if need to update then use Eq.(10).
Step 2.2.3: Update velocity according to Eq.(3).
Step 2.2.4: Update position according to Eq.(4).
Step 2.2.5: Update *fitness(i)*.
Step 2.3: Choose other N players from *PNum* population and play game.
Step 3: Output the fitness, position of each player in the population.

Figure 2. Procedure of the PSO algorithm

IV. Results

In the model we have analyzed, the effect of network structure to the evolution in most of the simulations. In the original model where punishment was not considered [21], an extended study concerning all the relevant parameters (including the distance between each node) of the corresponding model was presented. In this part, the effects of network structure to the evolution of cooperation are presented. Table 3 shows the symbols will be used in this paper.

Table 3. List of symbols used in the model

Symbol	Definition
PNum	Population size
N	Group size
c	Cost of helping
b	Benefits
r	Cost-to-benefit ratio ($0 \le r \le 1$)
β	Cost of being punished
γ	Cost of punishing ($\gamma < \beta$)
x	$\gamma = x * c$
y	$\beta = y * c$

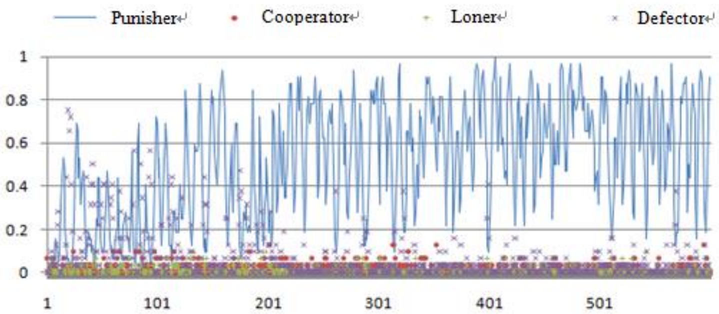

Figure 3. Proportion of each role in ISD game.

In order to keep the uniform distribution of choices during the initialization process, each choice is set to players with the same probability. For each iteration, players are chosen for the game, and the average payoff is calculated between players as fitness to choose strategy. Figure 3 shows the proportion of four roles of the player with *b=4, c=1*.

A. Levels of cooperation with punishment under small-world network

In this set of experiments, we compare equilibrium proportions of cooperators with punishment for n-ISD game as a function of the cost-to-benefit ratio $c/b \in [0 \dots 1]$. The punishment of *x=0.1* and the cost of punishment *y=0.1* are fixed, by varying c/b for comparison.

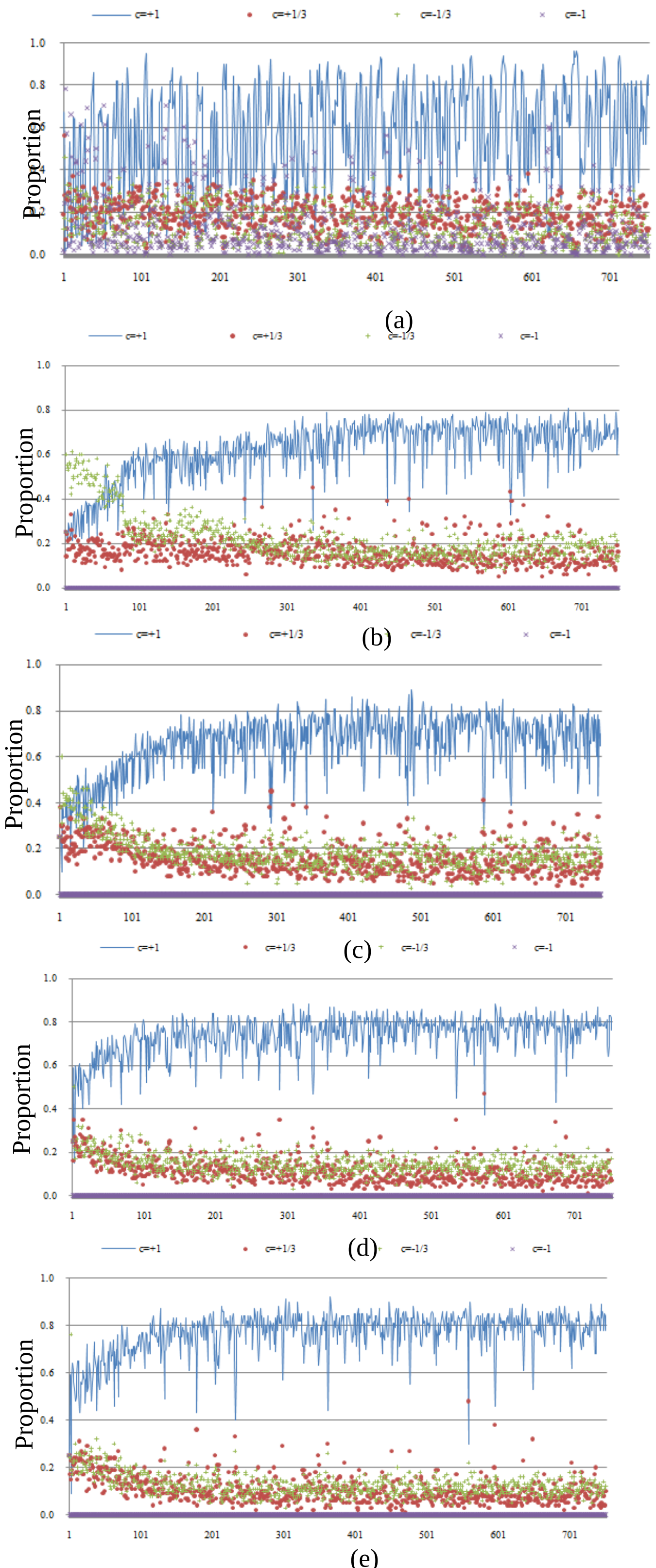

Figure 4. Proportion of four roles with different *c/b*, (a) *c/b*=0.8;(b) *c/b*=0.7;(c) *c/b*=0.5;(d) *c/b*=0.3;(e) *c/b*=0.1.

Compared with our previous research [21], the punishment can promote the mutualisms of the population, and the proportion of cooperators (include moralists) even reach the completely dominated state with small *c/b* ratio in ISD game (see Figure 3 and Figure 4). The frequency of cooperation is promoted with the increment of punishment intensity. Combining with these observations, it is clear that punishment is effective in promoting cooperation for a small cost-to-benefit ratio.

B. Levels of cooperation with different punishment

In this set of experiments, the affection of punishment is tested carefully, Figure 5 compares the punishment to the group cooperation and four parameters are tested. From these curves, we find the higher punishment, the more cooperation. The levels of cooperation are also affected by the cost-to-benefit ratio. As the increase of the value of *c/b*, the average cooperation is decreasing too. However, the decrease of cooperation ratio is also very serious when *c/b>0.5*, the same as Figure 5 shows.

Conversely, compared with the case without punishment mechanism, defection is better promoted by punishment (see Figure 5). The centralized punishment pattern allows the punishment of cooperators to be more competent. Punishment is always favored as the exploitation and the centralized punishment of cooperators.

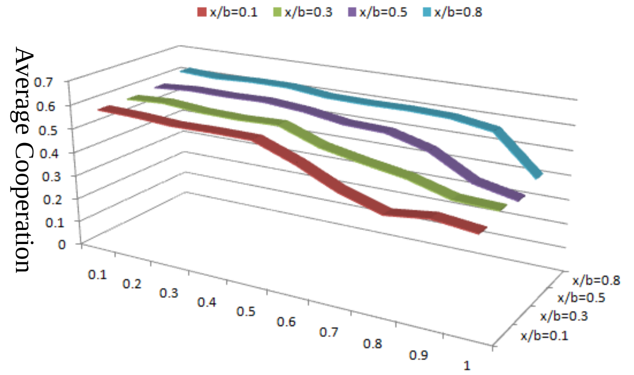

Figure 5. Average cooperation ratio under different punishment and cost-to-benefit ratio.

Figure 6 shows the proportion of four kind individuals during the iteration when punishment *x/b=0.5*, from the figures, it is clear that punishment has played an important role in the high level of cooperative behavior achieved previously. The value of cost-to-benefit *c/b* from 0 to 1, for each *c/b*, the iteration is 200 times. Compared with our previous studies [21], the proportion of moralist and cooperator become large when certain punishment exists.

C. Levels of cooperation with different cost of punishment

Figure 7 shows the average cooperation under different parameters of the cost of punishment. The cost of punishment to the defectors is paid by moralists. From the curves of this figure, we can find as the cost increased, the average cooperation decreased. This mainly because if moralists find the cost of punishment is too heavy to cooperation, they would choose to be the defectors.

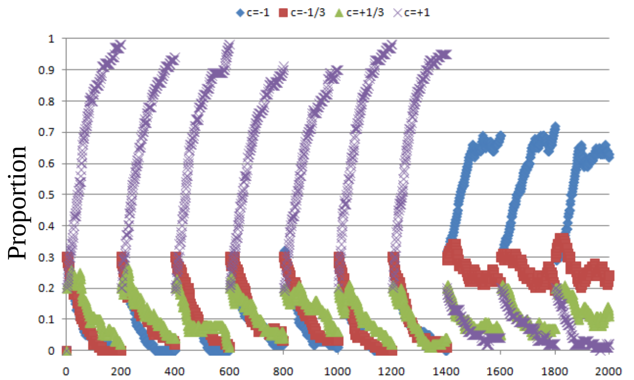

Figure 6. The proportion of four kind individuals during the iteration in iterated ISD game when punishment *x/b=0.5*. The *x* axis shows the proportion of four roles (i.e. defector, loner, cooperator, punisher) and the *y* axis shows the time. Colors correspond to the roles of four participators. The value of cost-to-benefit *c/b* from 0 to 1. For each *c/b*, the iteration is 200 times.

Compared with Figure 5, the average cooperation decreases quickly when *c/b* increases, and almost no cooperation if *c/b=1*. The reasons why the cost of punishment can decrease the cooperation so quickly need to be explored. In complex project cooperation, the profits are occupied by the system. All the cooperators want to find the "free-riders" in the system, however, if the cost of the finding process too heavy, no more moralists will exist. The "free-riders" find no one will punish them, more and more individuals will choose defection.

Figure 8 shows the proportion of four kind individuals during the iteration when cost-of-punishment *y/b=0.3*, from the figures, it is clear that cost-of-punishment has played an important role in the high level of cooperative behavior achieved previously. The value of cost-to-benefit *c/b* from 0 to 1, for each *c/b*, the iteration is 200 times. Compared with our previous studies [21], the proportion of moralist and cooperator become large when certain cost-of-punishment exists.

D. Levels of cooperation with multi-player iterated interactions

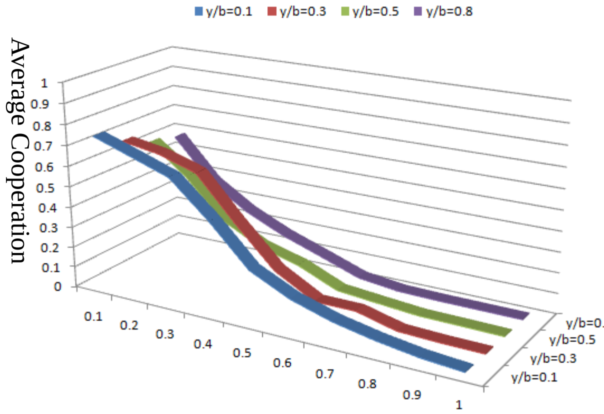

Figure 7. Average cooperation ratio under different cost of punishment and cost-to-benefit ratio.

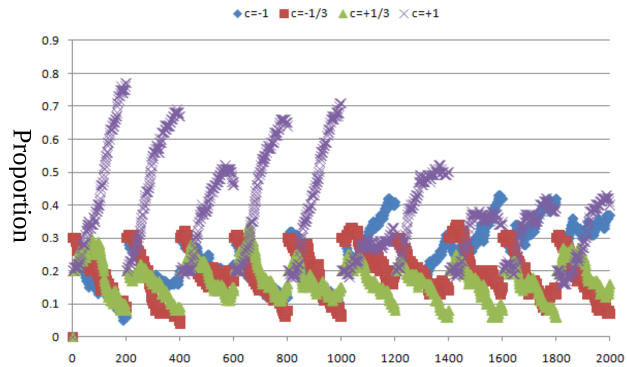

Figure 8. The proportion of four kind individuals during the iteration in iterated ISD game when cost of punishment *y/b=0.3*. The *x* axis shows the proportion of four roles (i.e. defector, loner, cooperator, punisher) and the *y* axis shows the time. Colors correspond to the roles of four participators. The value of cost-to-benefit *c/b* from 0 to 1. For each *c/b*, the iteration is 200 times.

From previous section, we find the punishment can evolve cooperation. It is well-known that the number of group size will affect the evolution of cooperation. To probe further on this issue, we repeated the simulation experiments across different group sizes ranging from *3* to *6*, fix the punishment-to-benefit *x/b=0.5* and the cost-of-punishment *y/b=0.05*.

Figure 9 shows the average cooperation ratios during the evolution; while Figure 10 shows the average cooperation ratio with different cost-to-benefit ratio *c/b* from 0 to 1. From these curves, we would find the cooperation will decrease as the number of group increased. This may because more individuals in the group, more debuts about each other exist. Players in the large group need to spend more time to make decisions about the action. In small group, the average cooperation can almost reach 100%, however, in large group, the average cooperation cannot reach 100% no matter how the punishment being.

When in the network structured population, it is more clear that the full cooperation state can emerges in the punishment mechanism even the punishment *x/b* or the cost-of-punishment *y/b* is not very high. The simulation results also uncovered an interesting phenomenon regarding the intimacy of individuals: the punishment can more evolve the cooperation than the cost-of-punishment. As the agents in the population would not willing to pay more.

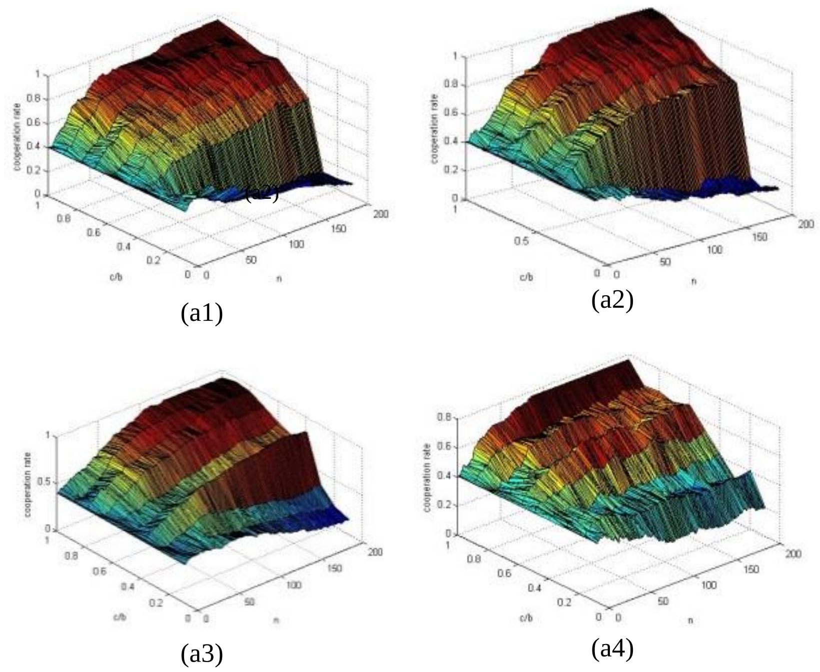

Figure 9. The distribution of the cooperation ratios in the network structures of ISD game with punishment *x*=0.5. Different group sizes are used for testing, (a1) n=3; (a2) n=4; (a3) n=5; (a4) n=6.

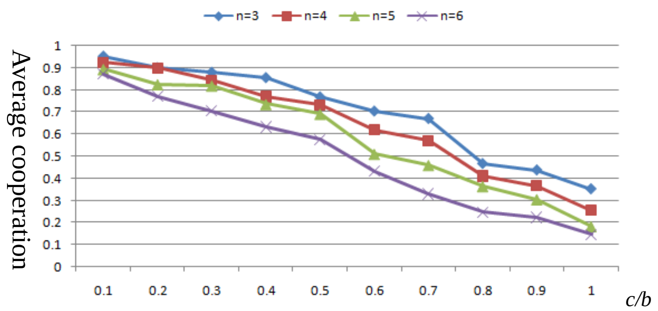

Figure 10. The average cooperation ratios in network structure of ISD game with different group size and *p/b=0.5* for each 200 iterations.

V. Conclusion and Discussion

The effects of punishment on the evolution of cooperation in multi-player evolutionary games: the spatial *n*-ISD game, are the main topic of our paper. Systematic computational experiments across a range of cost-to-benefit ratios and group sizes clearly showed that the punishment in spatial populations can promote higher levels of cooperation. Our model demonstrates, for a relatively small cost-to-benefit ratio *c/b* or for a relatively small group, that punishment *x/b* is effective in promoting cooperation. When in the network structured population, it is more clear that the full cooperation state can emerges in the punishment mechanism even the punishment is not very high.

Compared with previous research, the network structure did some good effect to the cooperation of ISD game. In addition, the full cooperation state can emerge in the spatial punishment environment, while the full cooperation state can hardly appear when no mechanism carried out.

The punishment can promote the mutualisms of the population, and the proportion of cooperators (include moralists) even reach the completely dominated state with small *c/b* ratio in ISD game (see Figure 7 and Figure 8). The frequency of cooperation is promoted with the increment of punishment intensity. Combining with these observations that, it is clear that punishment is effective in promoting cooperation for a small cost-to-benefit ratio (see Figure 4-8). In addition, another interesting finding is that punishment *x/b* seems more effective than cost-of-punishment *y/b* although the difference is not very clear.

For multi-player participate in the project, individuals need to carefully make decisions for each interaction. For large group size, the time for decision is longer than with small group size. So the cooperation in large group size is lower than in the small group size.

Furthermore, we explore the reasons of why punishing is effective to cooperation. Humans and other animals show, in the short run, amplified awareness and respond promptly with a drive towards self-regulation [52]. In this specific case, this drive is exerted with a more circumstantial adaptation to an environment occupied by willing cooperators. The Industry-university-institute cooperation, the punishment can give the organization or individual a long run negative effect. Finally, once you get the punishment no matter from whom, you may have a bad reputation for the following interactions.

While we have tested a broad range of conditions in our simulation experiments, there is always further scope for more investigations. The next step would be to extend our model to consider more about the punishment mechanism and the mobility of the network structure.

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