

A Self-Adaptive Policy Designed For Fruition of Support in Spread Networks

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ABSTRACT

In the Smart Technology people take more interest on Iterated game. A Self Adaptive Strategy is an evolution of Cooperation in Distributed Network. The Iterated game distribution network, having multiple selections game. In each selection, a player gains a payoff by playing a game, with its neighbors and updates its action based on the action or payoff of its neighbors. Our system has a theoretically finding about the proportion of co-operator. The interaction model between players is usually represented as a two-player, two-action Prisoner's Dilemma game. The system developed a iterated game to increase ratio of co-operators and also improve performance efficiently.

1. INTRODUCTION

It is well known that in unstructured populations, natural selection favors defectors over cooperators. In the real-world, who-meets-whom is not random, but determined by spatial relationships or social networks. There has been much interest in studying the evolution of cooperation in distributed networks. In these studies, the Prisoner's Dilemma (PD) game is the leading metaphor for the evolution of cooperation in populations of selfish players, especially since Axelrod's well known computer tournaments. In each round, two players engaged in the iterated PD game have to choose between cooperation and defection. If both cooperate, both earn Reward R as payoff, which is larger than payoff P , the Punishment that they receive if they both defect. However, if one player opts for defection and the other for cooperation, the defector receives payoff T , which is larger than R , while the cooperator's payoff S is even smaller than P . It is often furthermore assumed that the two players earn more if both cooperate than if they choose different options and then share the total payoff, which implies that $2R > T + S$. Thus, in a single round, the best option is always to defect, but in the iterated PD game, cooperation may be a better choice.

The evolution of cooperation among selfish individuals is a fundamental issue in a number of disciplines, such as artificial intelligence, physics, biology, sociology and economics. It has also been employed in industrial applications. For example, Wang and Nakao used the evolution of cooperation to drive an overlay network structure to a given topology. Lin et al. adopted the evolution of cooperation for data-aggregation in wireless sensor networks (WSNs).

Theoretically, it is well known that in unstructured populations, natural selection favors defectors over cooperators. However, in the real-world, who-meets-whom is not random, but determined by spatial relationships or social networks. Recently, there has been much interest in studying the evolution of cooperation in distributed networks. In these

studies, the Prisoner's Dilemma (PD) game is the leading metaphor for the evolution of cooperation in populations of selfish players, especially since Axelrod's well known computer tournaments.

In each round, two players engaged in the iterated PD game have to choose between cooperation and defection. If both cooperate, both earn Reward R as payoff, which is larger than payoff P , the Punishment that they receive if they both defect. However, if one player opts for defection and the other for cooperation, the defector receives payoff T (the Temptation), which is larger than R , while the cooperator's payoff S (for Sucker) is even smaller than P . It is often furthermore assumed that the two players earn more if both cooperate than if they choose different options and then share the total payoff, which implies that $2R > T + S$. Thus, in a single round, the best option is always to defect, but in the iterated PD game, cooperation may be a better choice.

Currently, several strategies have been proposed to increase the proportion of cooperators in the iterated PD game. The most famous strategy is the Tit-For-Tat (TFT), where each player cooperates in the first round and then adopts the behavior used by its opponent in the former round. A TFT player concurs with cooperators and retaliates against defectors, but a TFT player also forgives those defectors that switch to be cooperators. Thus, although TFT is quite simple, it does encourage cooperation among players.

However, TFT suffers from a stochastic perturbation, namely that occasional mistakes between two TFT players cause long runs of mutual retaliation. In order to overcome this drawback, two revised versions of TFT were developed: Tit-For-Two-Tats (TF2T) and Generous TFT (GTFT). A TF2T player allows two consecutive defections before retaliating. A GTFT player chooses cooperation after an opponent's cooperation but still uses cooperation, with a certain probability, after an opponent's defection.

Later, Nowak and Sigmund claimed that their strategy, Win-Stay, Lose-Shift (WSLS), outperformed TFT in the iterated PD game. A WSLS player maintains its action (which can be cooperation or defection), only if its current payoff is at least as high as in the former round. Frean devised a strategy called Firm But Fair (FBF). An FBF player is 'firm' in that it retaliates by defecting if it was a sucker in the previous round. An FBF player is also 'fair' in that it does not retaliate against a defector if it defected in the previous round as well, and it cooperates with suckers rather than continues to exploit them.

The Nowak and May presented a strategy, called Imitate-Best-Neighbour (IBN) (also known as Best-Take-Over), where each player imitates the action of the player (including itself), which achieves the most payoff in the former round. Another strategy, devised by Tang et al., is that in each round, a player selects a neighbour, based on the 'degree' of each neighbour, and then probabilistically adopts the selected neighbour's action, based on the payoff difference between itself and the selected neighbour. Here, the term 'degree' means the number of neighbours that a player has. The Santos et al. proposed a strategy named Stochastic Imitate-Random- Neighbour (StIRN), which is similar to Tang et al.'s strategy. In StIRN, a player randomly selects a neighbour in each round. The player imitates the selected neighbour's action, with a probability based on their payoff difference, only if, in the former round, the payoff of the selected neighbor was greater than the player's payoff.

Later, another stochastic imitate-random-neighbour strategy was developed. The strategy in is almost the same as Santos et al.'s strategy. The only difference between the two strategies is that the method used to calculate the probability of imitating a neighbour's action is different.

The strategy developed in is more suitable to multi-level networks than Santos et al.'s strategy. Hofmann et al. developed a strategy, called Imitate-Best-Strategy (IBS), where

each player sums the payoffs of all cooperating neighbours and the payoffs of all defecting neighbours (including itself) in the former round, and copies the action, which achieves the greater total payoff. Hofmann et al. also experimentally studied some of the existing strategies in the simultaneous PD game, and analysed their advantages and limitations. Based on Hofmann et al.'s analysis, it can be seen that the results of the evolution of cooperation, i.e., the final proportions of cooperators, derived by different strategies depend heavily on the initial proportion of cooperators and on the network type. For example, strategy IBS can increase the proportion of cooperators only when the initial proportion of cooperators is greater than 0.6; strategy WSLs can augment the proportion of cooperators only when the initial proportion of cooperators is less than 0.5; strategy StIRN can advance the proportion of cooperators only in a scale-free network. These dependency relationships limit the applicability of these strategies.

In order to overcome the dependency relationships of existing strategies, in this paper, a self-adaptive strategy is proposed. Selfadaptation, as a method to self-adjust the setting of control parameters, has been used in evolutionary algorithms to bias the distribution towards appropriate regions of the search space—maintaining sufficient diversity among individuals in order to enable further evolvability. However, to the best of our knowledge, this paper is the first one in the literature which uses self-adaptation in evolution of cooperation.

The proposed self-adaptive strategy includes existing strategies as each player's knowledge and enables each player in each round to autonomously select a strategy from its knowledge base to update its action and play with its neighbours. The advantages of the proposed strategy include that: (i) it is flexible because new strategies can be added into players' knowledge base and the strategies which already exist in players' knowledge base can be removed if necessary; (ii) the proposed strategy can sufficiently utilise the strengths of existing strategies and can avoid their drawbacks, because in the proposed strategy, if a strategy in a player's knowledge base does not work well in the current situation, that strategy will be assigned a very low probability for selection in the next round. Moreover, currently, most research on the strategies for evolution of cooperation has been done only experimentally. Raghunandan and Subramanian theoretically studied the relationship between the topology of a network and the sustainment of cooperation in a society of myopic players in an evolutionary setting, but they did not theoretically study the strategies used for evolution of cooperation.

In this paper, we theoretically study the strategies for evolution of cooperation and find that the final proportion of cooperators, derived by any deterministic strategies, in simultaneous and strictly alternating games, fluctuates cyclically. This finding is independent of the initial proportion of cooperators, the topology of a network, and the specific game. The proposed self-adaptive strategy and the theoretical finding are claimed as a two-fold contribution of this paper.

2. DISTRIBUTED COMPUTING

Distributed computing is a field of computer science that studies distributed systems. A distributed system is a software system in which components located on networked computers communicate and coordinate their actions by passing messages. The components interact with each other in order to achieve a common goal. Three significant characteristics of distributed systems are: concurrency of components, lack of a global clock, and independent failure of components. Examples of distributed systems vary from SOA-based systems to massively multiplayer online games to peer-to-peer applications.

A computer program that runs in a distributed system is called a distributed program, and distributed programming is the process of writing such programs. There are many alternatives for the message passing mechanism, including pure HTTP, RPC-like connectors and message queues.

A goal and challenge pursued by some computer scientists and practitioners in distributed systems is location transparency; however, this goal has fallen out of favor in industry, as distributed systems are different from conventional non-distributed systems, and the differences, such as network partitions, partial system failures, and partial upgrades, cannot simply be "papered over" by attempts at "transparency"

Distributed computing also refers to the use of distributed systems to solve computational problems. In distributed computing, a problem is divided into many tasks, each of which is solved by one or more computers, which communicate with each other by message passing.

2.1 EVOLUTION OF COOPERATION

The evolution of cooperation is one of the most discussed problems of evolutionary game theory. It has been studied in many contexts such as biology, sociology and ecology for many years. To study this problem, the prisoner's dilemma (PD), an evolutionary game introduced by Rapoport and Chammah, is often chosen because it gives a simple framework to understand this problem. This game is based on the fact that it pays off to defect. Defectors can take advantage of cooperators.

In this game, classical evolutionary game theory showed that defection is the evolutionary stable strategy. A mutation of defector will take over a population of cooperators but a mutation of cooperator can't survive in a population of defectors. This raises an important question: how can cooperation evolve in this situation? Why do we see cooperation in nature? Many attempts have been made to understand this question.

There are five main rules for the evolution of cooperation in the population. The first is kin selection. Natural selection can favour cooperation if the players are genetically related. Another rule is group selection. If the selection process is in group level. Natural selection will favour the group of cooperators. Another powerful mechanism is direct reciprocity. It expresses the idea that if you help me, I will help you and if you cheat, I will punish you. Using the PD game, Axelrod showed that cooperation can evolve in an environment consisting of individuals with selfish motives if the game is repeated. He organized two tournaments to find out the best strategy in an iterated prisoner's dilemma game. The famous simple strategy "tit for tat" won both tournaments. The PD game of Axelrod is the PD with memory and complicated strategies.

The fourth mechanism is indirect reciprocity. If we consider direct reciprocity to be a barter system when players trade directly with each other, indirect reciprocity is a monetary system. The player can help other players and get a good reputation, if he cheats, he will get a bad reputation. Other players will tend to play with the one who has high reputation. The final mechanism is spatial reciprocity. It can be generated to network reciprocity. Because the interaction is in space so the players who live near each other will interact more often with each other. Nowak, in his paper, showed that spatial effects can promote the coexistence of cooperators and defectors in the population. He showed that a simple spatial model of the prisoner's dilemma can "generate chaotically changing spatial patterns, in which cooperators and defectors both persist indefinitely". His initial model is a lattice model which is a two-dimensional cellular automaton and his result seems to depend

on the symmetry of the cellular automaton. Latter he did expand his model to spatial irregularities (random distribution of players) and probabilistic winning.

The main purpose of this project is to study this PD game in an irregular spatial model with diffusion of players. We use an irregular spatial model with diffusion to understand the dynamics of the system of cooperators and defectors. We keep the model as simple as possible. There are no memory (one shot game) and no complicated strategy.

Each player will only be either a cooperator or a defector and they are randomly distributed in the area which is a square length $L \times L$. Each player only interacts with neighbouring players in a radius r . At each time step, every players will play the PD with its neighbours and then collect scores. Then, each player will look at its neighbours and copy the strategy of the one with the highest total score.

We will consider both deterministic update rule and probabilistic update rule. With deterministic update rule, the player with lower score will always copy the strategy of its neighbour who has highest score. With probabilistic update rule, this player can keep its strategy with a small probability $1-p$. We also include mutation.

There is a small probability m that a cooperator become a defector and vice versa. Finally, each player will di_use by jumping a distance d from its initial position with a random direction. This will make sure that the space is really irregular and more realistic. We study the dynamics of the system using both synchronous and asynchronous updating.

2.2 THE PRISONER'S DILEMMA MODEL

The game we use to investigate the evolution of cooperation in spatial model is the prisoner's dilemma. This is a two-player game. Each player will be either a cooperator (C) or a defector (D). The score each one receive after each encounter is depend on this payoff matrix:

	C	D
C	R	S
D	T	P

If both players cooperate, they get a "reward", R payoff. If one player defects and the other chooses to cooperate, the defector gets the "temptation" payoff T and the cooperator gets the "sucker's", S payoff. If both players defect they both get the payoff P, "punishment".

With $T > R > P > S$, we can see the dilemma of this game: because $R > P$, mutual cooperation is better than mutual defection but because $T > R$ and $P > S$, defection is the dominant strategy. No matter which strategy the other player choose, it is better for the player to choose to defect. This will lead both player to choose to defect and they will end up in mutual defection which has lower score than mutual cooperation.

Mutual defection is a Nash Equilibrium. According to the traditional evolutionary game theory (one shot and non-memory), the evolutionary stable strategy (ESS) is defection. One defectors in a "sea" of cooperators will finally take over the population but one cooperators in a sea of defectors cannot survive. Many attempts has been taken to find the conditions in which cooperation can be maintain in this game. Axelrod and Hamilton showed that repeated with memory prisoner's dilemma can lead to cooperation. Nowak showed that a simple spatial model can also give rise to the maintenance of cooperation.

3. PROPOSED WORK

The first one in the literature which uses self-adaptation in evolution of Co-operation. The proposed self-adaptive strategy includes existing strategies as each player's knowledge and enables each player in each round to autonomously select a strategy from its knowledge base to update its action and play with its neighbour.

It is flexible because new strategies can be added into players' knowledge base and the strategies which already exist in players' knowledge base can be removed if necessary.

The self-adaptive strategy is given in Algorithm 1 in a pseudocode form. The essence of the self-adaptive strategy is that it includes existing strategies into each player's knowledge base. Then, in each round, each player autonomously selects a strategy to update its V_j action and plays with its neighbours. The knowledge of a player, say player V_j , is represented as $S_j = (S_1, \dots, S_m)$, where each $s_i \in S_j$ an existing strategy. S_j is also called the strategy set of player V_j .

Algorithm 1: The Self – Adaptive Strategy

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while (The Game is not Over) do
  for (Each player  $V_j$  in the network) do
     $V_j$  selects a strategy from its knowledge base ;
     $V_j$  plays the game with its neighbors and gets a payoff  $P_j$  ;
    for each strategy  $s_j$  in  $V_j$ 's knowledge base do
       $Q(S_i) \leftarrow (1 - \alpha) \cdot Q(S_i) + \alpha \cdot P_j$  ;
       $\pi(S_i) \leftarrow \pi(S_i) + \beta \cdot (Q(S_i) - \gamma \cdot \bar{P}_j)$  ;
     $\Pi \leftarrow \text{Normalize}(\Pi)$ 

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Where, $\bar{P}_j = \frac{\sum_{i \in N_j} P_j}{|N_j|}$

where $|N_j|$ means the number of elements in the set N_j . β is the probability (policy) adaptation rate, which is in the range of [0,1]. γ indicates how important a player's neighbours' average payoff is for that player's probability adaptation, and γ is in the range of [0,1].

This algorithm is a direct policy search algorithm, which learns stochastic policies. The stochastic policies can work better than deterministic policies in partially observable environments (such as the evolution of cooperation in distributed networks, where each player has the information only about its neighbours). This algorithm encourages each player to select the strategy, which is associated with a payoff higher than the average payoff of its neighbours, but this algorithm also forces each player to keep exploring non-optimal strategies

Self-adaptation, as a method to self-adjust the setting of control parameters, has been used in evolutionary algorithms to bias the distribution towards appropriate regions of the search space maintaining sufficient diversity among individuals in order to enable further resolvability.

4. CONCLUSION

In this paper, a self-adaptive strategy for evolution of cooperation was proposed, which includes existing strategies as players' knowledge and enables each player to autonomously select a strategy to update its action to play the game. In this way, the proposed strategy can avoid the flaws and can harness the advantages of each strategy. Furthermore, the proposed strategy is extendable, because newly developed future strategies can also be included as a new piece of knowledge into each player. The experimental results demonstrated the good performance of the proposed strategy in a number of situations. In addition, the theoretical analysis of deterministic strategies for the evolution of cooperation in various games was also given. In the future, we will attempt to develop a more complex and efficient learning algorithm to enhance the self-adaptive strategy. In this paper, the self-adaptive strategy has been tested in the PD game.

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