DRIS: Direct Reciprocity Based Image Score Enhances Performance in Collaborate Computing System

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Abstract. The key issue in collaborate computing systems is to induce agents work together towards a common task. Indirect reciprocity is a widely used method to promote cooperation. Image score is a classic indirect reciprocity mechanism which provided an insight on promoting cooperation. However, intuitively, people trust their own feelings more than other's opinions. Thus, in this paper, we introduce direct reciprocity into image score: when granting a service, a player should consider their own interaction histories in priority and consider image score if they have no interactions before. Extensive simulation results show that our proposed model can more effectively promote cooperation than classic image score under both complete and incomplete information.

Keywords: Direct reciprocity · Indirect reciprocity · Evolutionary game · Collaborative computing

1 Introduction

Cooperation is ubiquitous and plays a significant role in nature, human society and economy [1]. In collaborative computing system, such as distributed computing systems, P2P systems, etc., agents need to work together towards a common goal [2]. Without cooperation, the systems will eventually collapse. Thus, designing mechanisms to promote cooperation becomes a critical issue.

Direct and indirect reciprocity are two important mechanisms to promote cooperation [3].

The theory of direct reciprocity is first proposed by Trivers in 1970s [4]. In direct reciprocity mechanisms [5], each agent a records transaction histories with another agent b. If b cooperated with a in the last transaction, then a cooperates with b in this transaction. The famous competition held by Axelord further proved that direct reciprocity could promote cooperation [6]. However, direct reciprocity is a weak mechanism. It relies on repeated interactions between two individuals.

Indirect reciprocity mechanism [7,8] is also called reputation-based mechanism. It considers an individual's overall performance in a population [9].

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There is a trusted entity to help record each agent's reputation, which reflects how trusted an agent is. Agents with higher reputation have greater chances to be cooperated by other agents in following transactions. Image score [10] is a classic model for indirect reciprocity. In this model, image score is such an overall reputation value. Individuals consider recipient's image score before granting a service.

However, in real world interactions, people not only consider direct transaction histories, but also listen to other peoples' opinions. Thus, the combination of direct and indirect reciprocity is an interesting field.

In recent years, the combining of direct and indirect reciprocity draws lots of attention [11–16]. Gilbert Roberts [11] established a framework in which each individual uses one either direct indirect reciprocity and individuals evolve. It showed that direct reciprocity performs better when there were fewer individuals and more interactions. Meanwhile, indirect reciprocity alleviates the problem of lacking of interaction histories. Although, this paper gave an insight on combining direct and indirect reciprocity, it still didn't provide a complete simulation or theoretic model to clearly show how to combine these two mechanisms.

In our previous work [16], we proposed a hybrid trust model based on EigenTrust. In this model, recipient utilizes a two-phase reference method to take both indirect reputation and direct trust of a file provider into consideration before downloading. However, indirect reputation and direct trust work in different stages respectively.

In this paper, we propose a novel mechanism, which combines direct and indirect reciprocity in the same phase. Specifically, when an agent a gets a request from another agent b, a first considers b's direct transaction histories: if b granted a service to a before, then a grants a service to b in this transaction. Otherwise, agent a grants a service to b according to agent b's image score.

The contributions of this paper are as follows:

(1) A novel model combining direct and indirect reciprocity is proposed to promote cooperation.
(2) The decision making process is first considering direct transaction histories and indirect reciprocity information comes late, which helps to reduce accidental injuries to cooperative agents.
(3) Extensive simulations show that our proposed model promotes cooperation much more effectively than image score under both complete and incomplete information.

The rest of paper is organized as follows. In Sect. 2, we introduce our model in detail, including image score and our proposed model: DRIS. In Sect. 3, simulation results and some brief discussions are presented. In Sect. 4, we conclude this paper.

2 Model

2.1 Transaction Game

In this paper, we consider a collaborative system which provides resource provision services. In one transaction, one agent sends a request to a potential service provider, then the provider decides whether to grant a service or not. Thus, we abstract this process of transaction into a donor game.

A donor game is between two agents. One agent i plays as a service recipient and the other agent j plays as a donor. As shown in Table 1, if donor j grants a service, then the recipient i gets a payoff p and donor bears a cost c. Otherwise both players get a *zero* payoff. In donor game, it requires that $p > c$.

Table 1. Payoff matrix

	Donor	
Recipient	C	D
	$(p, -c)$	(0.0)

2.2 CIS: Classic Image Score

In image score, each agent i is assigned a strategy $S_i \in S$, where S is an available strategy set, $S = \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6\}$ and $S_i = -5$ represents fully cooperation, $S_i = 6$ represents fully defection. Each agent i has an image score $R_i \in R$, which reflects agent i's reputation. The set R is a set of available image score values and $R = \{-5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5\}$.

We consider a well-mixed population where each pair of agents can interact with each other. In one single game, a donor j gets a request from recipient i. The donor j first compares its strategy S_j with the recipient i's image score R_i, and donor j grants recipient i a service if $S_j \leq R_i$. If the donor j grants a service, its image score $R_j = R_j + 1$, otherwise, $R_j = R_j - 1$.

2.3 DRIS: Image Score with Direct Reciprocity

In DIRS, each agent i records direct transaction information towards agent j, DR_{ij}. In one single game (as shown in Fig. 1), donor j first checks its direct reciprocity DR_{ji}, if $DR_{ji} > 0$, which means i helped j before, then donor j fully cooperates with i; if $DR_{ji} < -2$, which means i defected on j more than twice, then donor j defects; otherwise, donor j considers its strategy S_j, i's image score R_i and the direct reciprocity DR_{ji}. If $S_j \leq R_i + DR_{ji}$, donor j cooperates, Otherwise, donor j defects. If donor j grants a service, then its image score $R_j = R_j + 1$ and $DR_{ij} = DR_{ij} + 1$; otherwise, its image score $R_j = R_j - 1$ and $DR_{ij} = DR_{ij} - 1$.

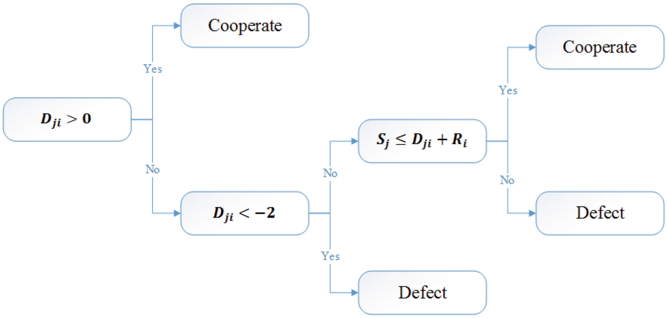


Fig. 1. Decision making of DRIS

To analyze the effect of direct reciprocity on image score, we consider two scenarios: (1) complete information and (2) incomplete information.

Complete information refers that one game can be seen by any other agents in the population. Thus, player i's image score R_i is shared a global variable and can be updated by all the agents in the population.

Different from complete information, incomplete information assumes that interactions between two agents are observed by only some of the agents in the population which are called observers. If no observer exists, image score is equal to direct reciprocity; if the proportion of observers equals to 1, then the model is equivalent to complete information. In each single game, observers are chosen randomly. Only observers and the recipient can update their perceptions of the donor j's image score.

2.4 Implementation of CIS and DRIS

The implementations are follow discrete time steps. As shown in Algorithm 1, the implementations are divided into $Tmax$ generations. In each generation, m games are played. After each game, information is updated. After each generation, agents reproduce their offspring with probability ρ_s. As shown in (1), the probability of agents with strategy s reproduces offspring (ρ_s) is proportional to its payoff P_s (see Table 2) over the total payoff of the system. Mutation refers to that some agents may change their strategies with a probability MR rather than its parent's strategy.

$$\rho_s = \frac{P_s}{\sum_{j \in S} P_j} \tag{1}$$

The implementation under incomplete information is shown in Algorithm 2. The main differences are in observer selection and information update. The observers are chosen randomly and only observers and the two agents in this transaction update their information.

Algorithm 1. Implementation under complete information

```
for Generation = 1 to Tmax do
    for steps = 1 to m do
        (a_j,a_i)= Random-choose()
        Game(a_j,a_i)
        Information-update(a_j,a_i)
    end for
    Statistic-payoff()
    Evolve()
    Mutation(MR)
end for
```

Algorithm 2. Implementation for incomplete information

```
for Generation = 1 to Tmax do
    for steps = 1 to m do
        (a_j,a_i)= Random-choose()
        Random-choose-observers()
        Game(a_j,a_i)
        Information-update(a_j,a_i,a_o1,...,a_on)
    end for
    Statistic-payoff()
    Evolve()
    Mutation(MR)
end for
```

Table 2. Definition of notations

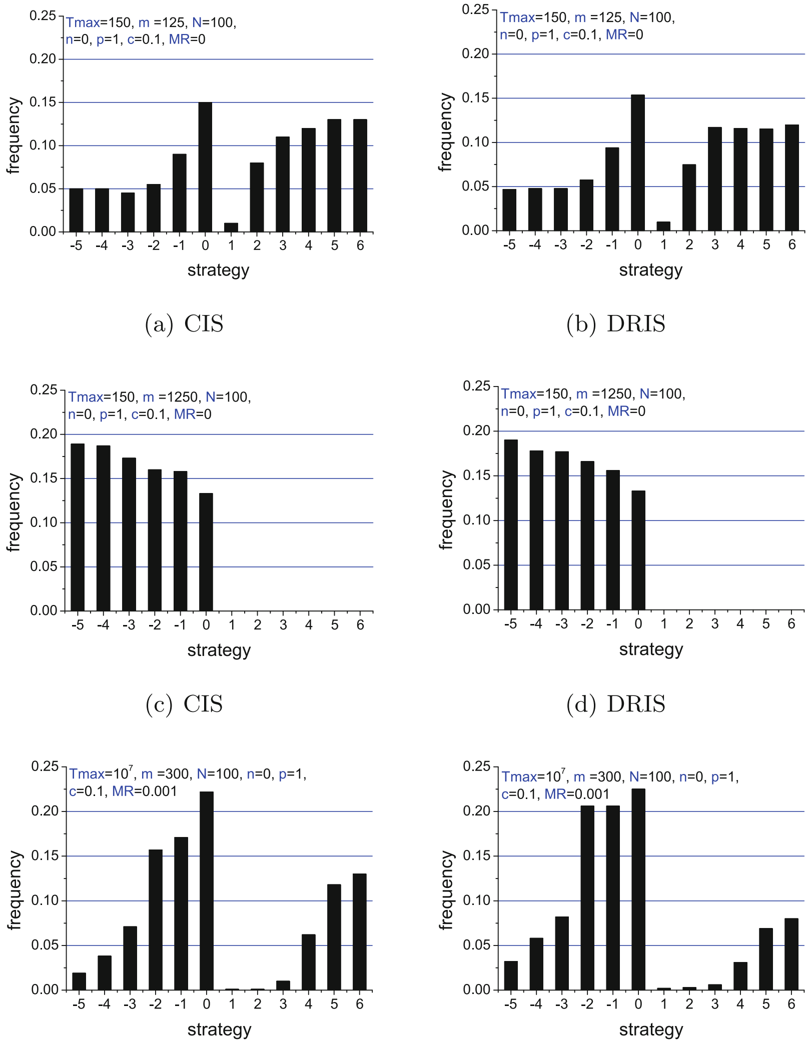
Notation	Definition	Notation	Definition
$Tmax$	The number of evolution generation	m	The number of interactions
N	The number of individuals	n	The number of observers
c	Donor's cost in one game	p	Recipient's pay-off in one game
MR	Mutation rate	P_s	The total payoff of strategy s
ρ_s	The probability of reproducing offspring		

3 Simulation Results and Analysis

We perform simulations in a well-mixed population with N agents. In each simulation, we mainly consider the effectiveness of the mechanisms from three aspects: distribution of strategies, the average strategy and the average payoff of all players. Each of the results is derived from the average result out of 10^5 times of simulations.

3.1 Complete Information

We first consider the scenario under complete information. In Fig. 2, each value represents the probability of the strategy being the evolutionary stable strategy (ESS). As shown in Fig. 2(a)–(d), without mutation, no matter how large the total number of transactions is, our proposed model (DRIS) has similar performance as classic image score model (CIS). However, as shown in Fig. 2(e)–(f), when we consider mutation in this system, our DRIS performs better that CIS on promoting cooperation: the proportion of cooperative agents is larger than that in CIS.



(a) CIS (b) DRIS

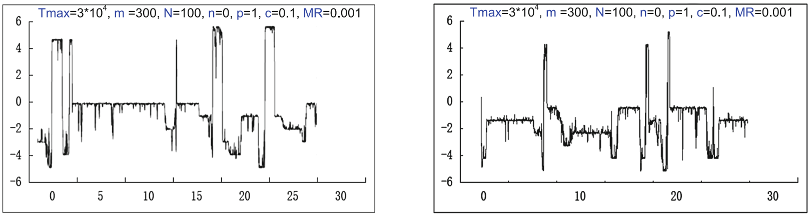
(c) CIS (d) DRIS

(e) CIS (f) DRIS

Fig. 2. Strategy frequency distribution at stable status under complete information

Under complete information, all of the transactions are visible. In this case, direct reciprocity is almost equivalent to indirect reciprocity, and the information is enough for CIS working. Thus, we get similar results. However, when mutation exists, direct reciprocity can resist the defective strategies generated by mutation and DRIS works a little better.

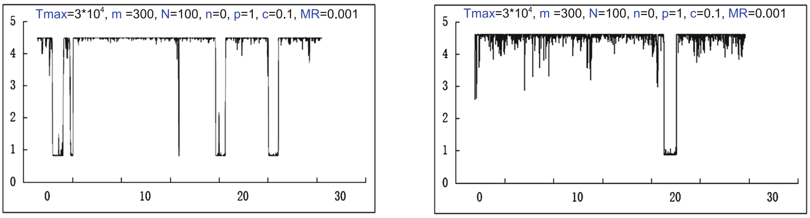
From another perspective, the average strategy dynamics is shown in Fig. 3. The average strategy is more frequently below 0 in DRIS (see Fig. 3(b)), which means our model is more effective on promoting cooperation.



(a) CIS (b) DRIS

Fig. 3. The average strategy dynamics under complete information

From the perspective of system benefit, we compare the dynamics of system average payoff. As shown in Fig. 4, our model can always have greater benefits than the classic model. Thus, our model is more effective on getting the system more profitable.

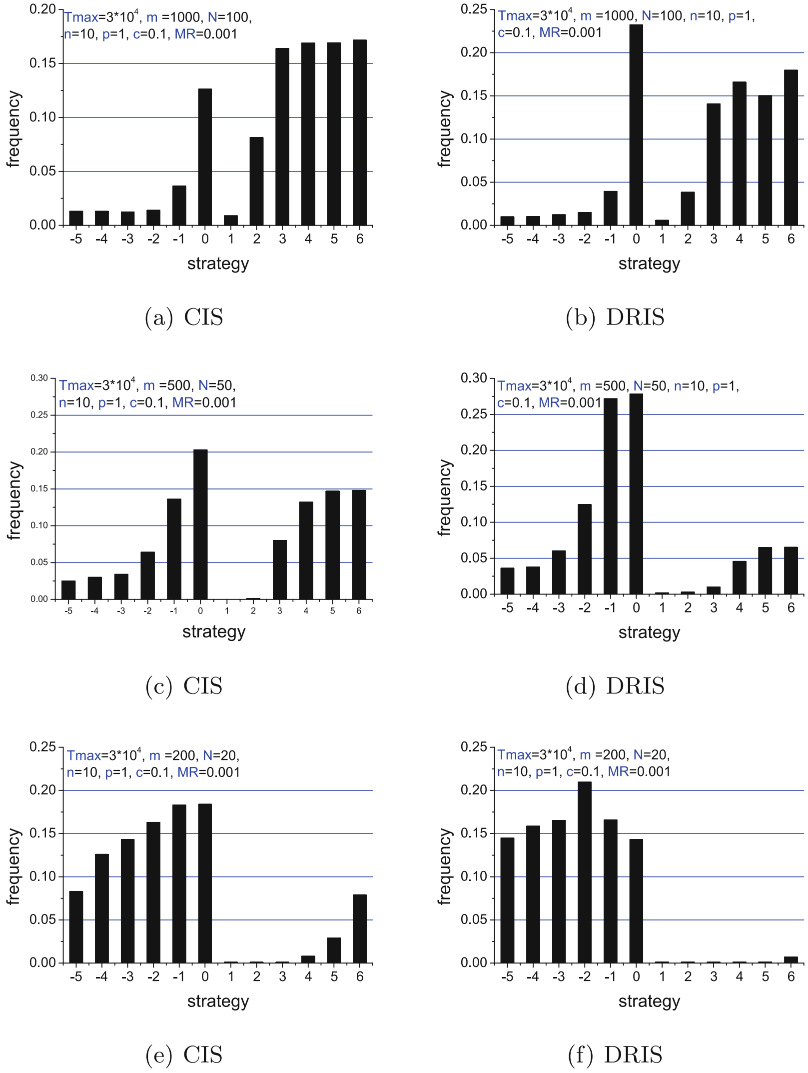


(a) CIS (b) DRIS

Fig. 4. The average payoff with complete information

3.2 Incomplete Information

In this section, we present the effectiveness of our model under incomplete information. The major simulation results are similar to that under complete information. Thus, in this section we present the influence of observer proportion on promoting cooperation under incomplete information. As shown in Fig. 5, as the proportion of observer increases, the situation is more similar to complete information, thus, the probabilities of cooperation being ESS increases. Still, our model is always better than classic model.



(a) CIS (b) DRIS

(c) CIS (d) DRIS

(e) CIS (f) DRIS

Fig. 5. Final strategy frequency distribution with incomplete information

Under incomplete information, image score is not accurate as the transactions are observed by only a few agents. Thus, direct reciprocity information is more feasible. It optimises the reputation and effectively improves cooperation among agents. Therefore, our proposed DRIS performs better than CIS.

4 Conclusion

In this paper, we present a novel model which introduces direct reciprocity into image score. Not only image score is considered when granting a service, but also direct reciprocity information. Simulation results show that under both complete information and incomplete information, our model is always better than the classic model on promoting cooperation and gaining system overall benefit.

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