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Heterogeneous cooperative belief for social dilemma in multi-agent system

Keke Huang[a,*], Xiaofang Chen[a,**], Zhaofei Yu[b], Chunhua Yang[a], Weihua Gui[a]

[a] School of Information Science and Engineering, Central South University, Changsha 410083, China
[b] Department of Automation, Tsinghua University, Beijing 100084, China

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ABSTRACT

In the multi-agent system, there exist many agents, which are often heterogeneous, so the same decision-making protocol is not suitable for all the agents. In addition, it is generally acknowledged that when agents update their behavior, they often have a prior cooperative belief. Motivated by these observations, we put forward a novel behavior learning strategy, which takes the cooperative belief distribution and imitation dynamics into account to solve the social dilemma in multi-agent system. By conducting large-scale Monte Carlo simulations, we can easily draw a conclusion that the proposed behavior learning strategy can promote cooperation efficiently. In detail, a larger weight of cooperative belief is more beneficial to solving the social dilemma when η is in a suitable range. Especially, when the weight of cooperative belief is large enough, the cooperative agents can overcome the negative feedback mechanism introduced by network reciprocity, and make cooperation be the dominating behavior directly. In addition, when the value of η is larger than the threshold, the cooperation promotion effect is not straightforward. Therefore, when confronted with agents with heterogeneous cooperative belief, we should balance the cooperative belief and imitation dynamics in the behavior learning strategy to purse the optimal cooperation phase.

1. Introduction

Multi-agent system is a complex system which consists of many agents with strong interrelationships. In the multi-agent system, the agents could be robots, humans or human teams [1–3]. In such a system, there exist a large number of selfish agents interacting with each other, since the resource is limited, the purpose of each agent often conflicts with the total purpose of the system, and the problem named social dilemma occurs. To resolve this dilemma, evolutionary game theory based methods are investigated [4–6], which have attracted extensive interest in the research of multi-agent system in order to study the emergence of cooperative behavior among selfish agents. Here, evolutionary game theory is the theory mainly about dynamic adaptation and learning in repeated games played by bounded rational agents. Typical examples of evolutionary game include repeated prisoners' dilemma and snowdrift game [7–9]. In the repeated prisoners' dilemma game, there exist two competing behavior: cooperation and non-cooperation, which is used as the paradigm for studying the resolution of social dilemma [10]. Traditionally, since the non-cooperative agents will get the highest fitness,

* Corresponding author.
** Corresponding author at: School of Information Science and Engineering, Central South University, Changsha 410083, China.
E-mail addresses: huangkekefendou@126.com (K. Huang), xiaofangchen@csu.edu.cn (X. Chen).

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the prisoners' dilemma game will completely fall into the pure non-cooperative phase when the network model is a fully connected network. However, cooperation is ubiquitously observed in the networked system, real world and different organizations ranging from microorganisms and animal groups to human societies [11,12]. In fact, social dilemma often arises in many situations in multi-agent systems, such as file sharing in P2P systems, wireless sensor networks and so on [13]. Therefore, understanding how agents can achieve cooperation in social dilemma in multi-agent system is of significance for the practical applications in the field of society, politics, biology, physics and engineering [14,15]. Mechanisms that promote cooperation in social dilemma are of great attraction for researchers in multi-agent system.

Solving the puzzle of how cooperative behavior evolves among interconnected agents is still an open question that has motivated researchers for decades [16,17]. The pioneering work was introduced by Nowak and May [18], which shows that the spatial structure enable the cooperative agents to form clusters to prevent the exploitation of non-cooperation agents. Within the framework of spatial evolutionary game, the interaction structure of agents can be modeled by other kinds of networks [19,20]. Santos and Pacheco have discovered that scale-free networks promote the emergence of cooperation in both the repeated prisoner's dilemma game and snowdrift game [21]. Recently, the interaction structure, which describes the interaction of agents, has been intensively studied as a paradigm for illustrating how cooperative behavior evolves, such as small-world network [22], hierarchy network [23], interdependent networks [24–27], and they have been proved valuable for solving the dilemma to some extent.

Generally speaking, the evolutionary game dynamics of multi-agent system consists of three fundamental factors: network model, game model and decision-making protocol [28]. For the decision-making protocol, agents update their behavior with a desire of better fitness. Since the perfect rationality is hardly satisfied for all the agents in a multi-agent system, the main behavior learning strategy is based on the imitation rules, such as Fermi rule [29,30], proportion rule [31,32], and adaptive rule [4,33]. However, as the multi-agent system consists of many agents, the agents are heterogeneous, such as the wealth and social status [34], aspirations [35], interaction environments [36] and so on. Therefore, one typical decision-making protocol is not suitable for all the agents. In addition, it is generally acknowledged that when the agents update their behavior, they often have a prior cooperative belief. Motivated by these two assumptions, we treat the decision-making protocol of multi-agent system as a behavior learning problem in this paper. In detail, the prior cooperative belief and imitation dynamics are taken into account at the same time to determine how individuals update their behavior, therefore, it is an incorporated behavior learning strategy. In this paper, we assume that the cooperative belief of one agent is randomly sampling from a truncated power-law distribution to describe the heterogeneous cooperative belief of agents in the multi-agent system.

The left paper is organized as follows. Section 2 introduces the evolutionary game dynamics including the proposed behavior learning strategy of the multi-agent system. Section 3 explores the emergence of cooperation as well as decision dynamics in the multi-agent system by large-scale Monte Carlo simulations. The concluding remarks are given in Section 4.

2. Evolutionary game dynamics of multi-agent system

In this section, we will introduce the evolutionary game dynamics of the multi-agent system. Generally, game dynamics on the multi-agent system consists of three fundamental factors: (1) the network model of the multi-agent system, (2) the game model between agents, and (3) the behavior decision-making protocol of each agent. Therefore, we can record an evolutionary game of the multi-agent system by a triple $\Gamma=(G, S, U)$, where $G=(V, E)$ is a undirected network, and $V=\{1, 2, \ldots, N\}$ is the agent set, $E\subseteq V\times V$ is the edge set which represents the interaction relationship between agents. S is the space of behavior in the evolutionary game, $s_v \in S$ is the behavior of agent v. U is the fitness function, which depends on the payoff matrix and the behavior of the focal agent and his directed neighbors. In general, the game dynamics include two steps. First, agents engage in an evolutionary game and obtain their payoff by interactions with the directed neighbors, and then agents adjust their behavior based on the fitness landscapes from the previous steps. In order to highlight the effect of the cooperative belief on the game dynamics, we assume that the network model of the multi-agent system is a regular network, and the number of agents is N, the number of directed neighbors of each agent is $k=8$. Apparently, the network model is just the same as the spatial cellular automaton with periodic boundary conditions. Here, the size of the cellular automaton is $L\times L$ $(N=L^2)$, and each agent will interact with his Moore neighbors.

In the interaction process, each agent chooses one of the two behavior: cooperation or non-cooperation in a pairwise game. The fitness of the each agent is determined by their behavior and payoff matrix. For example, in the tth step, if the agents 1 and 2 choose cooperation and non-cooperation, respectively, namely, $s_1(t)=[1, 0]^T$ and $s_2(t)=[0, 1]^T$, then, the payoffs of agents 1 and 2 are $P_1 = s_1^T(t)Ms_2(t)=0$ and $P_2 = s_2^T(t)Ms_1(t)=b$, respectively. After the agent interacts with his directed neighbors, the agent can obtain his fitness by the summation of all the payoffs. We assume that the fitness of agent x in the tth step is $U_x(t)$. Accordingly, the fitness can be obtained as follow:

$$U_x(t) = \sum\nolimits_{y\in N_x} s_x(t)Ms_y(t) \tag{1}$$

Here, $s_x(t) \in S$ is the behavior of agent x in the tth step, N_x is the set of neighbors of agent x, which is independent of time step. M is the payoff matrix,

$$M = \begin{bmatrix} R & S \\ T & P \end{bmatrix} \tag{2}$$