Physica A 436 (2015) 694–706

Contents lists available at ScienceDirect

Physica A

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

Evolutionary Minority Game with searching behavior

Wei Zhang, Yuxin Sun, Xu Feng *, Xiong Xiong

China Center for Social Computing & Analytics, College of Management & Economics, Tianjin University, Tianjin 300072, China

HIGHLIGHTS

- We introduce optimal neighbor searching and global searching on the Evolutionary Minority Game.
- The probability distribution of best strategies are different with searching behavior, as opposed to standard EMG model.
- The system performance becomes worse after adding searching behavior.

ARTICLE INFO

Article history:
Received 19 October 2014
Received in revised form 15 May 2015
Available online 27 May 2015

Keywords:
Evolutionary Minority Game
Searching behavior
Networks

ABSTRACT

In this paper, we determine the impact of searching behavior on the evolutionary minority game (EMG). We introduce searching behavior in two ways: optimal neighbor searching and global searching. Our study investigates the distribution equilibriums of probabilities that agents follow a given strategy and on system performance of the game. The results indicate that the distribution equilibriums of the probabilities are different with searching behavior, as opposed to without searching behavior. The system performance becomes worse after adding the searching behavior. Additionally, we test other variables in a standard EMG with and without searching behavior.

1. Introduction

In the Evolutionary Minority Game (EMG), agents compete for resources and are rewarded if they correctly select the minority strategy. Which strategy will be selected by an agent largely depends on the private information the agent has and the history record. In the early stage of standard EMG, agents can obtain aggregate information of all agents in the game and make decisions based on adaptive learning. After the network structure modeling is incorporated into EMG studies, agents can only obtain information from their neighbors, which is more similar to a real-world scenario.

Arthur, in 1994 [1], first proposed the El Farol Bar model to illustrate that "inductive thinking" and "adaptive learning (such as reinforcement learning or best-reply learning [2,3])" are more reasonable assumptions in complex economic systems. Ref. [4] was inspired by the El Farol bar model and investigated the emergence of cooperation and organization in the minority game. Johnson et al. [5,6] extended the MG to the evolutionary minority game. In the EMG model, each agent has only one strategy, which depends on his history experience. Ref. [5] introduced a gene parameter p that indicates the probability that an agent followed the reference table instead of forming distinct strategies in the MG. The population will tend to self-segregate into two opposite behaviors. In the standard EMG, agents have no direct interactions, while agents who behave in a risk-taking manner generally perform better than cautious ones [7,8]. Ref. [9] demonstrated that this dynamic segregation became more apparent and more robust if there was a slight change, causing the above-average adaptation strategies to become more frequent. Similar results appeared for a generalization of the EMG with more than two choices.

* Corresponding author.
E-mail address: fengxu@tju.edu.cn (X. Feng).

http://dx.doi.org/10.1016/j.physa.2015.05.096
0378-4371/

However, individuals can always exchange their information with each other in the real world [10,11]. Later studies consider local coordination and extend it to a fixed network EMG model. Under the fixed network structure, only local information can be known, which makes the simulation more consistent with the real market. Ref. [12] modified the EMG model such that agents were placed in the nodes of a ring, a torus, and a random graph, and the simulation results demonstrated that a better coordination (a lower frustration) could be achieved if agents based their actions on neighbors instead of on the global trend. Many types of network structures were employed in the EMG and MG models, such as a small-world network [13]. Ref. [14] introduced small-world interactions as local information transmission mechanisms. The agents are mapped to the nodes of the small-world network. The results suggested that agents coordinated their behaviors more effectively than in the standard EMG. Ref. [15] investigated star networks, regular networks, random networks and scale-free networks and also obtained similar results. Ref. [16] examined the response time and the mutation threshold of agents and found that highly adaptive agents (with short response times) perform best at the same time the "patient" agents (with high mutation thresholds) outperform "nervous" ones under the fixed network EMG model. Ref. [17] also found that agents' probability of winning produced oscillations with amplitude and frequency that depend on the value of R.

Our model is a dynamic network EMG model, rather than a fixed network EMG. Refs. [18,19] are most closely related to our study but they focus on the MG model. Refs. [18,19] focused on the payoffs of each agent, while our study focused on the probability distribution for agents acting based on strategy predictions (p-value) and on the performance of the entire economic system.

We considered the dynamic network in the form of "searching behavior", which can be observed as a more complex inductive learning process. In our model, the capacity of the information search for each agent is limited; only finite information sources can interact. When agents find the existing strategy cannot sustain positive payoffs, they will abandon the worst source of information and search for a new one to replace it. We introduce two sources of information searching methods: one searches from the past best performing neighbor for the "neighbor's neighbor" in the best performance and connects its source of information; another one searches randomly from the global agents to select the new agent as its source of information. The searching behavior in our model represents a more complex inductive learning behavior in the real world. For example, individuals with searching behavior can give up bad information sources and connect new information sources. Particularly in the era of the Internet and social media, such information searches and information update behaviors are more common and costless, which may change the balanced strategy of the EMG.

Compared with the standard EMG, the p-value has no significant change under the fixed network structure. Agents' strategies eventually form into segregation. Our research indicated that the segregation might be changed because of the searching behavior. Under these two searching behaviors, the strategy distributions do not form segregations, as under the standard EMG model or under the fixed network and are completely different. Furthermore, we also observed that an information searching behavior is not able to improve the overall welfare of all agents, and after joining the search, the overall welfare agent instead becomes worse.

The paper is organized as follows. In Section 2, we define and introduce in detail the EMG model and discuss how we improve this model to study for search ability. In Section 3, we present numerical results of our model and compare results without searching. In Section 4, we present our conclusions.

2. Model

2.1. The networked EMG model

The variable settings in our paper retain the standard EMG [5] and the fixed network structure [14]. In the networked EMG model, there are an odd number of N agents. Each agent must choose one group each from Group 0 and Group 1. All agents share the same reference table that records the outcomes for each turn and provides predictions for the next turn. The memory length is m, indicating there are 2^m possible outcomes. When m is equal to 3, the possible outcomes are 000, 001, 010, 011, 100, 101, 110, and 111. At the beginning of the game, the reference table will predict an outcome for the next period based on the history experience, such as 000(1), and the agent should choose whether to follow. In the example 000(1), the table predicted the next period minority group would be group 1 based on the history. If the outcome is 0 and not the same as predicted, the 000(1) will be updated to 000(0). At the end of each turn, those agents who select the minority group can receive one point as a reward, while other agents will lose one point as a punishment. The probability of an agent following the trend presented in the reference table is p. Agents make the opposite prediction with the probability $1-p$. We assign the p value as agent's strategy (known as gene value) [5]. Each agent can receive local information from his neighbors including a gene value p and scores.

If an agent's score falls below a threshold d ($d < 0$), which means the maximum number of tolerated failures for the current p-value, the agent's p-value will be mutated based on its neighbor with highest score. The new p-value is produced randomly from the internal $[p_{\max(s)} - r/2, p_{\max(s)} + r/2]$. The $p_{\max(s)}$ means the p-value of an agent with highest scores. When an agent's score fall below the threshold value d, it will look for an agent with highest scores nearby or randomly. The better the agent's strategy is, the higher scores the agent can win. So the agent with lower scores would like to learn the strategy p-value from the agent with higher scores. The r is the mutation magnitude. However, the value of p must be in [0, 1]; we employ reflective boundary conditions [5] with the set $0 \le r \le 2$. If the value is less than 0, we take the absolute value for the new p value. If the value is larger than 1, we provide that the new p-value must be equal to 2 minus randomly