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Adoption of Social Rules in Teams of Different Sizes

Hao Ji[1] , Yan Jin[*2]

[1]Department of Aerospace and Mechanical Engineering, University of Southern California

[2]3650 McClintock Ave. OHE-430, University Park, Los Angeles, CA, 90089-1453, USA

[1]haoji@usc.edu; [*2]yjin@usc.edu

Abstract

Organizational structuring has been an important subject in the fields of organization science and engineering management. Due to the highly complex task environment and inherently sophisticated structure of organizations, it is often difficult to observe details of how an organization's structure affects its performance. In computational studies of self-organizing systems, however, agents self-organize through a set of predefined rules for dealing with the dynamic changing environment and tasks. This offers a unique approach to gain insights on why and how structures evolve over time and how structuring impacts team performance under what conditions. In this paper, a computer simulation based study is carried out to explore the impact of social rules on the performance of self-organizing teams with various team sizes. The results have shown that stronger structuring favors team effectiveness in general for both small and large team sizes, while team efficiency under strong structuring peaks at a given team size and then decline with the increase of team size.

Keywords

Management of Organization; Self-Organizing Systems; Social-structuring; Rule Adoption Rate; Team Size

Introduction

Organizations employ different kinds of organization structures to deal with coordination problems and achieve their goals. According to Minzberg (1979, 1980, 1993), there are five basic structural configurations of organizations: simple structure, machine bureaucracy, professional bureaucracy, divisionalized form and adhocracy. Among these five configurations, professional bureaucracy takes a unique form in the sense that organizations are not centralized but attain a kind of bureaucracy (Minzberg, 1980; Lunenburg, 2012). This is important because such organizations are more robust to external changes of the environment and also to organization's internal changes such as employee turnover. In professional bureaucracy, organizations' behaviors are standard-ized by coordination mechanism of standardized skills, which allows an autonomy of work among its professionals (highly trained specialists) in the organizations' operating core (Minzberg, 1980; Lunenburg, 2012).

In case of teams, such as engineering project teams, social rules (i.e., coordination rules), and hence the structures resulted from these rules, are also important for achieving desired team performance. There can be multiple factors that influence the impact of social rules, including the content and amount of rules, the percentage of people who adopt or follow the rules, and the size of the team. The research question of this paper is: Given a set of social rules, how will the team performance be influenced by the interplay between the rule adoption rate (or percentage) and the team size?

To answer this question, a computer simulation based study is carried out to investigate how self-organizing systems evolve structures based on given social rules. In such self-organizing systems, generally speaking, agents have high adaptability to the task environment through self-organizing (Chen and Jin, 2011; Chiang and Jin, 2011; Zouein, Chang and Jin, 2011). This is achieved by predefining a set of rules for agents to follow. Each agent is allowed freedom to explore, exploit and solve complex task by themselves while at the same time, through mutual adjustment, agents interact with their task environment and with each other, leading to self-organizing emergent behavior and functions at the system level (Chen and Jin, 2011; Chiang and Jin, 2011; Zouein, Chang, and Jin, 2011; Levitt and James, 1988; March, 1991). During this process, agents achieve global coordination while accomplishing individual goals. Each agent makes their movement decisions completely based on its own sensed information of the environment, its own transformation algorithm, and its own decisions for action.

In this paper, we explore a dynamic social structuring approach in self-organizing systems. We attain social structuring among agents by introducing social rules and devising a social-rule based regulation for agents to choose their actions (Khani et al, 2016). In this approach, agent's behavior is adjusted through perceived social relations to be in harmony with system-wide welfare (Khani et al, 2016; Khani and Jin, 2015). Social rules can be designed based on the task definition and resolution of potential conflicts (Khani et al, 2016; Khani and Jin, 2015).

In the rest of the paper, related work is reviewed and dynamic social structuring concepts are introduced. And then, a social rule based self-organization approach for organization structuring with various team sizes is presented. Next, results are discussed on how social rules and team size affect organization's performance. At last, conclusions are drawn and future research directions are suggested.

Background and Prior Work

Research has been done in the past that looks into organization configuration, its related coordination mechanisms, its basic components and its evolution. Minzberg (1979, 1980, 1993) proposed five different configurations of the organizations, five coordination mechanisms, five basic elements of the organizations and elaborated on each of these five organization configuration's characteristics and applied areas. Lawler and Hage (1973) investigated into professional bureaucratic conflict and intraorganizational power-lessness among social workers by conducting an analysis of the data collected from interview of 144 social workers. Currie and Procter (2005) looked into how organizational performance can be affected by what is happening in the middle of the organization, rather than at the top. They argued that the role of middle managers in professional bureaucracy context is affected by limited factors. However, such conflict of role and ambiguity can be reduced by a process of socialization (Currie and Stephen, 2005). Other researchers examined organization from a different perspective. Levitt and March (1988) argued that organizational learning is routine-based, history dependent and target oriented. Originations learn through direct experience and from experience of others. March (1991) also came up with a mathematical model and identifies the relationships between two different kinds of organizational learning: exploration of new possibilities and exploitation of old certainties. And he found that exploitation helps more in the short run while exploration might benefit in the long run for organization evolution (March, 1991). Recently, organizational design has shown to be effective and is typically used to achieve better communication strategies (Horling and Victor, 2004). It has been proved that the behavior of the system depends on shape, size and characteristics of the organizational structure (Galbraith, 1977; Brooks, 2003; Durfee et al, 1987). Researchers have suggested that there is no single type of organization that is a best match for all circumstances (Galbraith, 1977; Durfee et al, 1987). Despite wide research in the organization science and social structuring, little research has been done on how organization structures evolve in self-organizing systems in which agents can perform complex task given a list of predetermined coordination rules.

In the system engineering and robotics world, there has been wide research on using multi-agent or multi-components to realize system level function and accomplish complex task (Ferguson and Lewis, 2006; Martin and Ishii, 2002). Fukuda and Nakagawa (1988) developed a dynamically reconfigurable robotic system known as DRRS. Unsal et al (2001) focused on creating very simplistic i-Cube systems (with cubes being able to be attached to each other) in order to investigate whether they can fully realize the full potential of this class of systems. PolyBot has gone through several updates over the years (Yim, et al, 2002) but acquired notoriety by being the first robot that demonstrated sequentially two topologically distinct locomotion modes by self-configuration. SuperBot (Shen, et al, 2006) is composed of a series of homogeneous modules each of which has three joints and three points of connection. Control of SuperBot is naturally inspired and achieved through a 'hormone' control algorithm. Despite the implicit and informal nature of some multi-agent relations, all multi-agent systems possess some form of organization.

To develop adaptive and complex systems, our previous work investigated box-pushing cases and has gained useful insights into how social rules affect self-organizing system's performance in different complexity level settings (Khani, et al, 2016; Khani, and Jin, 2015).

Social Rule Based Team Coordination

To develop a computer model of self-organizing systems to study team coordination, we take a social rule based behavior regulation approach and explore various local and bottom up social relations to achieve dynamic social structuring. Generally speaking, the deficiency of disorderliness or disorganization can be divided into two categories. One is 'conflict deficiency' and the other 'opportunity-loss deficiency'. For simple tasks where individual agents' 'goals' are mostly consistent with the system goal, the agents' effort can additively contribute to the system overall function. When tasks become more complex, conflicts between agents' actions may occur and cooperation opportunities may be lost. In order to minimize the conflict between agents and exploit cooperation opportunities, social rules and social relations can play an important role.

A social rule is a description of behavioral relationship between two encountering agents that can be used by the agents to modify their otherwise individually, rather than socially, determined actions. Two agents acting on a give social rule are said to be engaged in a social relationship.

Based on the definitions mentioned above, when agents are engaged in social relations by following social rules, social structures emerge, leading to more order of the system. To avoid conflicts and promote cooperation, social rules can be defined to specify which actions should be avoided and which actions are recommended for given conditions. The conditions are often task domain dependent, although some of them can also be general. We have,

Definition 1: (Social Rule): sRule = (C, ForbA, RecA) where C is a condition specifying a set of states; ForbA: forbidden actions for states specified by condition; RecA: recommended actions.

Definition 2: (Social Rule Adoption Rate): The probability of adoption of the social rules by each agent when any of the rules become applicable.

Definition 3: (Social Structuring): Dynamical employment of the social rules among agents leads to real time structured interactions among the agents in the self-organising system.

Definition 4: (Team Size): The number of agents within each simulation is considered the team size.

Social rules introduce relations among encountering agents. It is conceivable that when an agent encounter neighbors and neighbors encounter their neighbors the cascading effect may lead to a large scale network structure with varying density of connections.

To apply a social rule, an agent needs to

1) generate its independent action profile,
2) identify and communicate with its neighbors,
3) possess social rules,
4) know which rule to apply for a given situation,
5) know how to generate new socially compliant action.

Each of the 5 steps can be task domain dependent. The modelling details of these steps can be found in our previous work (Khani et al, 2016; Khani, and Jin, 2015). In the following section, we present a case study and explore social rule based self-organizing with various team sizes. We investigate how the change of social rule adoption rate among agents and team sizes affect the overall system's structure and hence performance.

Case Study: Search and Capture

In this paper, a case study on a 'Search and Capture' task is carried out. The objective of this case study is to gain insights on how social rule adoption rate actually affects the self-organizing system's performance with various team sizes. Moreover, the obtained insights should provide guidance for engineering team management. All the results of the study are the mean values of 300 simulations runs.

Tasks

The 'Search and Capture' task is illustrated in Fig 1. The blue human shapes are agents. The star shapes are targets. The targets with larger size are 'strong targets' and those with smaller size are 'weak targets'. Each target holds some amount of energy and each agent's goal is to search and capture the energy from the targets, trying to get the most of energy within a limited time (in this simulation, the limited time is defined as 100 ticks/steps of the simulation) and capture as many targets as possible.

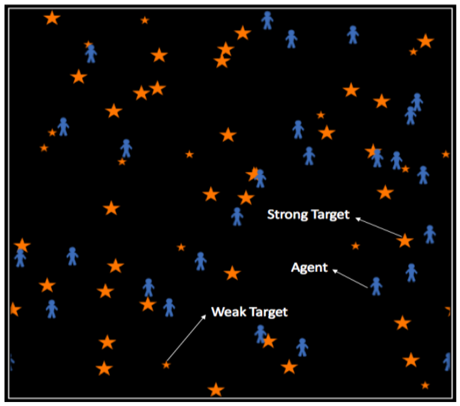

FIG. 1 EXPLANATION OF THE TASK OF 'SEARCH AND CAPTURE'

Attributes of Target and Agent

The two basic components of this self-organizing system are agents and targets. Each component has a number of attributes associated, which are shown in TABLE. 1.

TABLE. 1 ATTRIBUTES OF TARGET AND AGENT

Target Attribute	Agent Attribute
Number of Targets (50)	Team Size (10:10:50)
Location	Location
Energy (1 or 6)	Energy (+0 or +1 or +2)
Strength of Targets	Visibility Range (R5)
Capture Range (R2)	Communication Range(R5)
Targets Mix-up Rate (30%)	Social Rule
Color State (O, M, G)	Color State (Blue)
Visibility (50%)	Social Rule Adoption Rate (0%,10%,30%,50%,70%,100%)

Target Attributes

- Total number of targets: The total number of targets in this simulation is 50, including both strong and weak targets.
- Strength of target: There are two kinds of targets: strong targets and weak targets. Three agents are needed to capture a strong target, while only one agent is needed to capture a weak target.
- Energy of the targets: Strong targets have 6 units of energy and weak targets have 1 unit of energy.
- Location (x, y, dx, dy, angle): After the initial setup, targets are distributed at random locations on a squre plane; during simulation, targets move randomly in different directions.
- Visibility (V(t)): Targets have two different states: visible and invisible (to the agents). In our simulation, targets

become visible 50% of the time on a random basis. Specifically, when a target's color becomes orange, it is visible to the agents and when its color turns magenta, it is invisible to the agents.

- Capture Range: The radius of the circle around a target within which agents are able to capture the target. In our model, we define the capture range to be a radius of 2.
- Color State: As stated above, orange means targets are visible to the agents while magenta means not visible. Moreover, when target's energy is captured, its color becomes grey. In Table 1, O means orange, M means magenta and G means grey.
- Target Mix-up Rate: The percentage of weak targets among total number of targets is called target mix-up rate. In our simulation, 30% is used as the target mix-up rate.

Agent Attributes

- Team Size: The total number of agents. Team size varies with each set of simulations, from 10 to 50 with an interval of 10.
- Energy Captured (+1 from a small target, +2 from a large target, 0 if no captured target): Agents start with zero energy and gain energy by capturing energy from the targets. If a strong target is captured by 3 agents, each agent get 2 units of energy. If captured by more than 3 agents, agents do not get energy from the strong targets because of the overpopulation. If there are fewer than 3 agents within capture range, energy of the target is not captured. Meanwhile, if a weak target is captured, it immediately gives 1 unit of energy to the agent.
- Location (x, y, dx, dy, angle): After initial setup, agents are distributed at random locations. During simulation, agents move either randomly or based social rule depending on the rule adoption rate.
- Visibility Range: Agents are able to see targets within a visibility range of radius 5 circle. Agents can only see the targets that are visible to them (when the targets become orange) and are within the visible range.
- Communication Range: Agents are exchanging position information with each other inside the communication range, which is set to be the same as the visibility range.
- Social Rules: Agents move and communicate according to their social rule. Details of the social rules will be illustrated further in the next section.
- Social Rule Adoption Rate: When a social rule bcomes applicable, an agent has the option to follow or ignore the rule. The social rule adoption rate is the likelihood that agents will follow the social rule. In our simulation, social rule adoption rate ranges from 0%,10%,30%,50%,70% to 100%.

Actions of Agent

The detailed actions that agents perform can be categorized as follows:

A1 = <Find ><Target >
A2= <Distinguish ><Target >
A3= <Seek ><Help >
A4= <Capture ><Target Energy >
Each agent has its individual goal, which is to find targets and acquire the maximum amount of energy. However, since one agent is not able to capture strong targets by itself, they need to seek help from other agents. Cooperation arises when the agents are communicating between each other for the sake of their own interest. However, conflict also rises if they over-cooperate (i.e., when more than 3 agents capturing 1 strong target) or under-cooperate (i.e., less than 3 agents working on 1 strong target).

Social Rules: A Coordination Mechanism

Social rules are usually introduced to facilitate cooperation or avoid conflicts. In this case study, it helps agents cooperate and fulfill their mutual interests. Agents can see targets within their visibility range, broadcast their position information and ask for help from neighboring agents within their communication range. The communication rule is illustrated in the hierarchical decision tree in Fig. 2.

Meanwhile, agents make decisions whether to follow or ignore communication rules based on the social rule adoption rate.

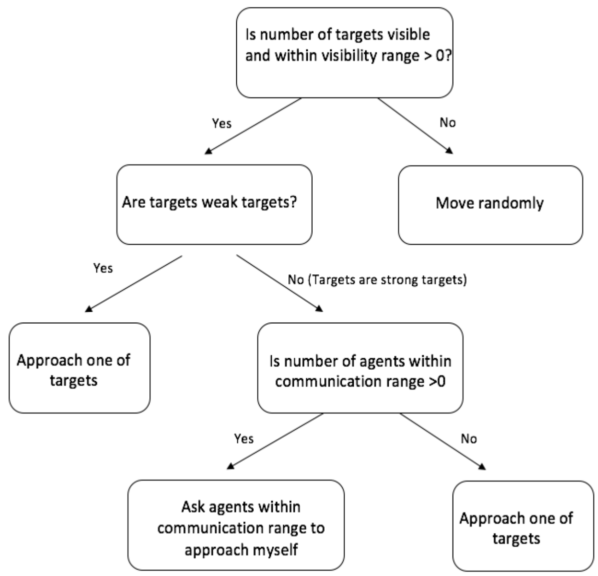

FIG. 2 HIERARCHICAL DECISIOIN TREE OF AGENTS

Performance Mearsure and Experiment Setup

In order to fully investigate the impact of social structuring on the self-organizing system performance, we measure performance of the system based on effectiveness and efficiency. For this case study, we choose the fixed duration of the simulation to be 100 tick times. Then, the overall system effectiveness is assessed by measuring the success rate—i.e., percentage of targets captured. Individual Efficiency is evaluated by measuring the average energy each agent captured. Fig. 3 shows the experiment setup for the 'Search and Capture' case study.

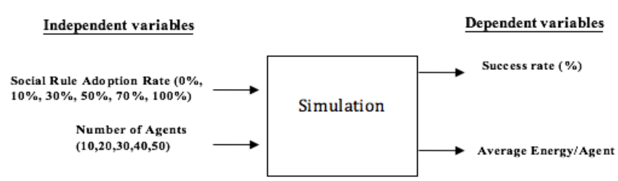

FIG. 3 EXPERIMENT DESIGN WITH TWO INDEPENDENT VARIABLES AND THREE DEPENDENT VARIABLES

- Success Rate: Success rate is measured by measuring the number of targets captured divided by the total number of targets.
- Average Energy/Agent: It is measured by sum of the energy captured by all the agents divided by the total number of agents.

The simulation was run under 'Netlogo', a multi-agent simulation software commonly used in simulating self-organizing system. Each individual test parameter was run 300 times to maintain the statistical significance of the simulation results and to avoid randomness of results introduced in each simulation. The final simulation result is an average mean value based on 300 simulation runs.

Results

Fig. 4 shows the screen shots of a typical simulation run when team size (number of agents) = 30. At time tick = 0, agents and targets are randomly distributed. At tick = 30, some small groups of agents are formed (which are shown in blue circle). At this time, social structuring and groups formation help agents capture the energy of the strong targets. At tick 50, more and larger groups are formed, which are shown in blue circle, and agents tend to stick to their groups without leaving. At tick = 100, most of the targets are captured, agent groups have a tendency to desolve and agents spread out more randomly across the plane, similar to the initial setup condition.

Fig. 5 shows the success rate comparison for various social rule adoption policies for the team of agents with various team sizes. Success rate measures the percentage of targets captured at the end of simulation run. As can be expected, as team size increases, success rate goes up accordingly. This is because the ’number’ advantage wins over and help the team better tackle the task. Also, when social adoption rate is increased at a given team size, there is an increase in the success rate, which means the larger social rule adoption rate helps agents better cooperate in terms of reaching overall goal of the system. So, strictly following social rules helps the team to form structures for achieving overall effectiveness. However, as team size becomes larger, the effect of social rule adoption diminishes due to overwhelming coverage of vast team size. So, it is not necessary to have an oversized team for reaching overall system effectiveness, since a smaller team size can already perform well.

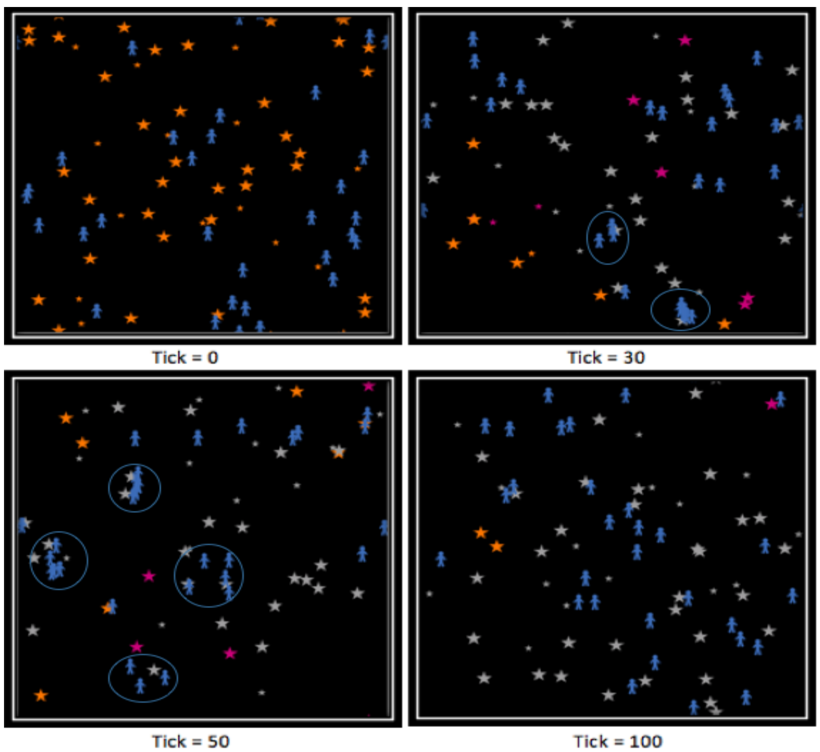

FIG. 4 SCREENSHOTS OF A TYPICAL SIMULATION RUN AT VARIOUS TICK NUMBERS WHEN TEAM SIZE IS 30

Fig. 6 shows that the average energy that each agent captures at the end of the simulation. As can be seen in the figure, increasing social adoption rate helps the average energy acquisition when team size is small. This is because the smaller the team size, the stronger need for cooperation in order to accomplish complex tasks. As the team size increases, it reaches a point where large social adoption rate does not help with the average energy capturing anymore. Specifically, after team size reaches 30, increasing social adoption rate actually weakens agents’ ability to acquire energy from the targets. We can also notice in this figure that for the same social adoption rate, increasing the team size has some beneficial effect on energy acquisition when team size is small (below 30). This means that given limited time (e.g. within 100 tick simulation run) and resources (eg. total energy in the simulation environment), it might be beneficial to increase team size and still benefit each team member at the same time.

However, when team size reaches 30, further increase in team size does not help individual agents acquire energies from targets. The worst case scenario is that when the team size reaches 50, there is a slight tendency that average energy captured by an agent goes down. So, in designing effective organization structures with limited resources, when team size becomes large, there are fewer individual gains. In summary, choosing an optimal team size is essentially important in forming organization structures. Teams with optimal size can not only benefit individuals but also help increase system effectiveness. Furthermore, the social rule adoption rate should also be carefully chosen in accordance with the team size.

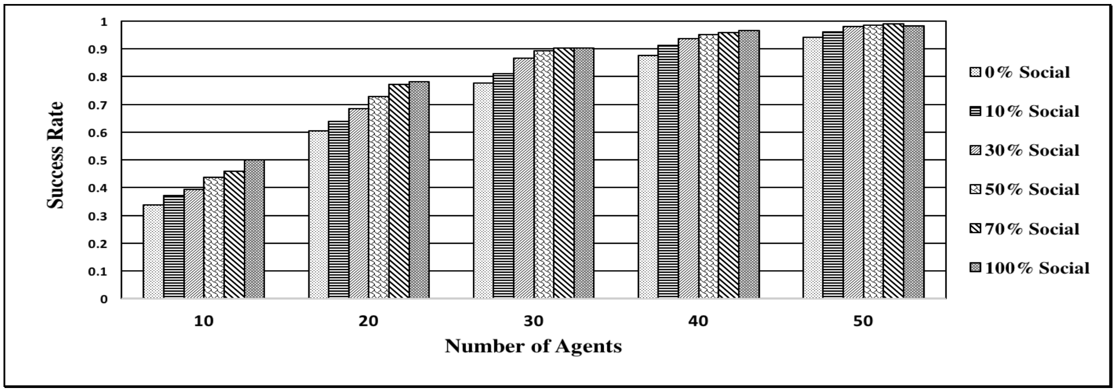

FIG. 5: SUCCESS RATE COMPARISON FOR VARIOUS SOCIAL RULE ADOPTION POLICIES FOR THE 'SEARCH AND CAPTURE' TASK WITH VARYING TEAM SIZES

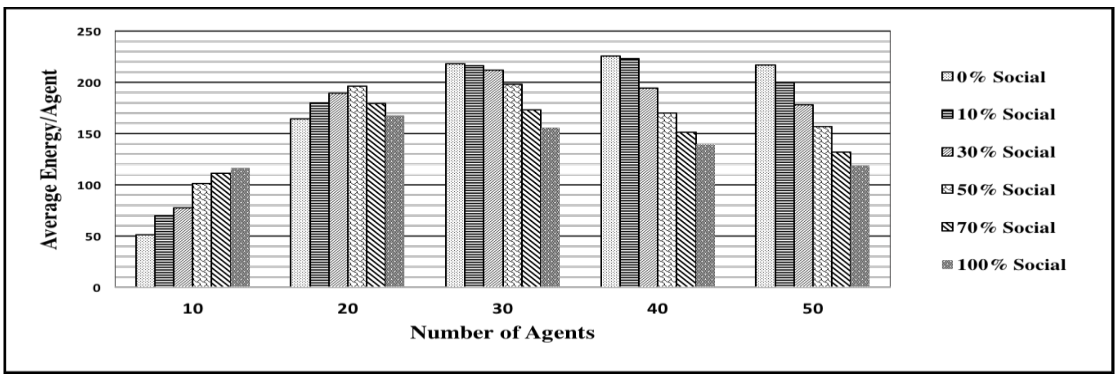

FIG. 6: ENERGY/AGENT COMPARISON FOR VARIOUS SOCIAL RULE ADOPTION POLICIES FOR THE 'SEARCH AND CAPTURE' TASK WITH VARYING TEAM SIZE

Conclusions

In this research, we explored the impact of social rules on the performance of teams with various sizes through a self-organizing search and capture case study. Specifically, we investigated on how changing parameters such as team size and social rule adoption rate influences team effectiveness and efficiency. The following conclusions can be drawn.

1). For overall system effectiveness (i.e., success rate):

a) Stronger social structuring helps agents reach better success rate when completing their tasks.

b) As team size becomes larger, the effect of social rule adoption diminishes due to overwhelming coverage of vast team size.

2). For individual efficiency (energy/agent):

a) When team size is small, increasing social rule adoption rate helps improve efficiency.

b) As team size increases, there is a transition point where the social rule adoption rate does not affect the efficiency of the team.

c) When team size becomes large, the social rule adoption actually decreases the efficiency of the system due to its overhead cost.

The overall recommendation for designing engineer-ing organization structure is that team size should be made neither too small nor too large. Also, given a team size, social adoption policy should be specially selected such that when team size is small, teams should work more specifically according to the social rules. When teams become larger, the social rules should only be loosely followed.

Our future work will address the issues arising from teams with heterogeneous agents, and expand the task domains by carrying out more case studies.

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Hao Ji is a PhD student in the Department of Aerospace and Mechanical engineering of University of Southern California. He abtained his Master's degree in University of California at Berkeley (2014). After graduation, he worked as an affiliate researcher in University of California Berkeley, investigating into tensegrity systems. He joined USC in Fall 2015 and his current research interest is simulating and analyzing organition structure through multi-agent systems.

Yan Jin is Professor of Aerospace and Mechanical engineering at University of Southern California. He is a recipient of the NSF CAREER Award (1998), the TRW Excellence in Teaching Award (2001), and the Xerox Best Paper Award (2002). He currently serves as Editor in Chief of AIEDAM journal and Associate Editor of Design Science journal. His current research focuses on organization modelling, self-organizing systems, and design creativity.