Valuation of Cooperation and Defection in Small-World Networks: A Behavioral Robotic Approach

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Abstract

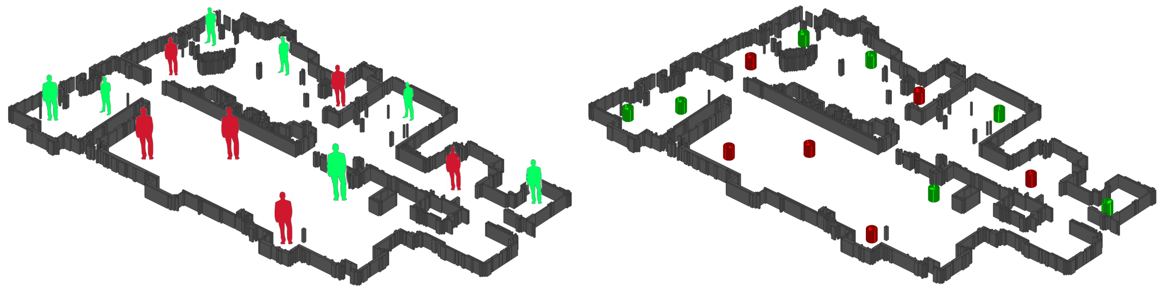
Valuation of behaviors in a social network is a very complex task due to dynamic nature of interactions, changes in behaviors and difficulties in defining the norms to evaluate the behaviors. Though, this valuation is a mandatory first step in studying evolution of behaviors in social networks. Therefore, in this paper two major game theoretical behaviors in social networks, namely *Cooperation* and *Defection* are programmed in members of a large group of robots. Various experiments on the multi-robot system are carried out to study the fitness of individuals who have adopted each of these behaviors in a *Small-World*-like environment compared to a *Regular* environment. The results of this study reveal one of the important characteristics of small-world networks in which individuals are not directly connected to one another, but have indirect links to every other via a small number of intermediate individuals: The more individuals adopt Cooperation in a small-world environment the less benefits they'll get in the group. In contrast, our results show that in regular environments where no short connection exists between most of the individuals, a reverse phenomenon is seen: The cooperators surpass defectors once they are in the majority. Such kind of results suggest that, by getting advantage of the proposed multi-robot framework, valuable contributions can be delivered to the field of social science.

1 Introduction

"Evolution of Cooperation" is a topic that seeks to provide an answer for why and how cooperators prevail in a society of selfish individuals. The systematic study of this topic dates back to the work of Axelrod and Hamilton in 1981 [3]. Despite of the very thorough study of this topic by Axelrod and Hamilton, many researchers from natural, social and computer sciences are still exploring this problem from different perspectives [15]. This shows the complexities and dimensions of this topic which is further increased by the emergence of social network models such as *Scale Free* and *Small-World* Networks [4, 20].

A central question in this line of research is which criteria play key roles in emergence and persistence of cooperation in social networks. For example in [18] the role of social diversities such as diversity in number of interactions, in increasing the cooperative behaviors is studied. In [13], the role of commitment strategy in reaching certain levels of cooperating behaviors in the network is studied. More recently, in [16] a theoretical framework based on Control theory is proposed for evolution of cooperation, and in [17] the intertwined evolution of behaviors and emergence of networks are studied simultaneously.

The physical environment and external disturbances can also play a key role in evolution of behaviors in social networks. However, studying the role of such criteria using theoretical frameworks and numerical simulations is very difficult and even infeasible in many cases. In contrast, behavioral sciences have the capability to systematically observe the effects of physical environment on individual behaviors (e.g., in [21]).



(a) Behavioral studies using human subjects

(b) Behavioral studies using robotic agents

Figure 1: A group of agents interacting in an office-like environment. The color represents specific type of behavior, and as agents meet in the environment they interact based on their behaviors. Consequently, according to the payoff matrix of a Game Theoretical setting each individual receives a payoff in form of acceleration or punishment in form of delay in movement.

In behavioral robotics, as an alternative approach to traditional behavioral sciences, robots can be used in experiments where the physical environment or properties of the physical environment are likely to influence the outcome of social behaviors [5, 10, 14]. For instance, Keller et al. [14] have shown that robots can be used to study the self-organization, communication, the evolution of cooperative and competitive behaviors.

Therefore, in this paper we use a group of robotic agents to valuate the cooperation and defection behavior (i.e., the first step to study evolution of cooperation) in a small-world setting. A framework is proposed, as shown in Figure 1, in which robots move randomly in an environment. Whenever two robots are close to each other and are in line of sight of each other, they start playing a simple game in which each agent can either defect or cooperate. Based on the Prisoner's Dilemma game, the punishment and payoffs are embedded in form of delays and accelerations in movements, respectively. Consequently, the average speed of individuals is used to measure the fitness (value) of each individual in the group. Compared to existing multi-robot platforms for studying behaviors in social settings (e.g., in [5]), the proposed framework is easier to implement and is easier to be extended to other social experiments.

The rest of the paper is organized as following: First, the preliminary information are provided in Section 2, then the methodology used to propose the behavioral robotic approach is introduced in Section 3. Experiments on two different type of environments are provided in Section 4 and discussions on results and concluding remarks are provided in Sections 5 and 6.

2 Preliminaries

In this section we introduce the elementary background on Game Theory and Social Networks which have formed the foundations of this work.

2.1 Game Theory

Game theory models strategic interactions in the form of games. Each player has a set of actions, and a preference over the joint action space that is captured in the received payoffs. The goal for each player is to come up with a strategy that maximizes his expected payoff in the game. A strategy that maximizes the payoff given fixed strategies for all opponents is called a best response to those strategies. The players are thought of as rational, in the sense that each player purely tries to maximize his own payoff, and assumes the others are doing likewise. Under this assumption, the Nash equilibrium concept can be used to study what players will reasonably choose to do. A set of strategies forms a Nash equilibrium if no single player can do better by unilaterally switching to a different strategy [9].

The prisoner's dilemma is a canonical example of a game. In this game, two players have the option of either cooperating with the other or defecting. The players have to decide simultaneously what to do, given that they do not know their opponents decision. In this game, the best solution for both players is to cooperate and receive a low reward, however individually both are tempted by the higher payoff of defection, leaving the other with the sucker punishment. As both reason like this, they end up in the less favorable state of mutual defection, receiving a punishment, hence the dilemma.

2.2 Social Networks

Networks, in the most general sense, can be seen as patterns of interconnections between sets of entities [8]. These entities make up the nodes in the network, whereas the edges represent how those entities interact or how they are related. A social network is a type of network where the nodes represent a set of social agents (e.g., individuals in a society or firms in a market) and the interconnections between the nodes, represent a set of ties between these agents.

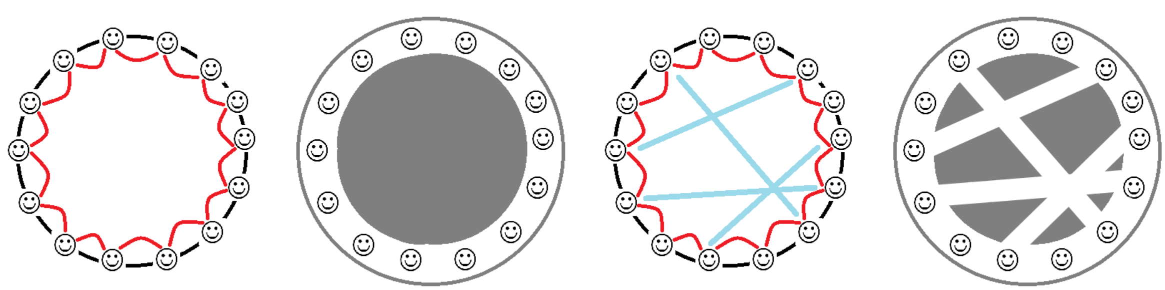
Based on the structural properties of a social network, different network models are already proposed: In a *regular* network all nodes have exactly the same degree (i.e., the same number of connections to other nodes). For instance, a ring is a regular network of degree 2, and a complete network is a regular network of degree $n-1$, where n is number of nodes. Another model used to describe real-world networks is the *small-world* model, that is characterized by short average path lengths between nodes and high clustering [20]. In small-world networks most nodes are not direct neighbors of one another but still can mostly be reached from every other by a small number of steps. A small-world network model provides a realistic representation of social networks.

3 Methodology

This section details the multi-robot behavioral framework proposed in this paper. First, the environment design inspired by social network topology is described, then the game theoretical definitions are provided, and finally the robot behavior design is explained.

3.1 Environment Structure

As described in Subsection 2.2, network models can represent the topological structure of relations between individuals. However, in real world environments where individuals continuously change their interactions, and consequently their neighborhood changes, such models cannot be directly used. Therefore, we propose an environment map corresponding to each network topology as shown in Figure 2.



(a) Regular Network (b) Regular Environment (c) Small World Network (d) Small World Enviornment

Figure 2: Network topologies and their corresponding environment map.

As can be seen in Subfigure 2(b), in a regular environment agents are more constrained to move within their local neighborhood; moving to far locations and meeting some other robots requires traversing a long distance. In contrast, in Subfigure 2(d) the shortcuts between different regions of the small-world environment allow agents to reach different locations and meet most of other robots by traversing a short distance.

The proposed structures for environment map, namely *regular environment* and *small-world environment*, capture the main characteristics of their corresponding network model: A low number of immediate neighbors for individuals can be seen in both networks. Besides, most individuals need to traverse a long distance to meet each other in the former environment. In contrast, individuals can mostly meet each other by traversing the shortcuts provided in the latter environment.

3.2 Game Theoretical Definitions

In the proposed framework, each robot is considered as a *Player* and the whole experiment, in which robots move randomly and interact whenever they face each other, is considered as a multi-player *Game*. The *Strategy* of the players is defined as the main interaction policy that they use when they face each other:

- *Cooperation*: A cooperating robot avoids collision with other robots by turning and changing its movement direction.
- *Defection*: A defecting robot moves straight ahead toward other robots, and ignores the possibility of collision.

The *fitness* of each robot is defined as the average absolute speed of the robot over time. Specifically, the fitness for the i^{th} robot at k^{th} time steps is given by

$$F_i = \frac{1}{k} \sum_{j=1}^{k} \frac{\left| P_i(j+1) - P_i(j) \right|}{\Delta t} \tag{1}$$

where $P_i(j)$ is the position of robot i at iteration j, Δt is sufficiently small equal to the time step in experiments, and $|.|$ denotes the distance between two points in a 2D plane.

3.3 Behavior Design

In order to implement the game theoretical setting introduced in previous subsection on robotic agents, robots should be programmed to follow a set of behaviors that each will be activated in different situations.

First of all every robot is programmed to do a *random walk* in the environment, while avoiding collisions with obstacles.

The second behavior is an *interaction behavior* which is activated whenever two robots face each other directly and are close enough to play the game. In this case two robots head for a single passway from opposite directions. Therefore, the first robot which swerves leaves the passway to the other robot. If neither robot swerves, robots will bump into each other (or at least get stuck in a very close distance). It is thus the best chance for defectors to stay straight while the cooperator swerves. Additionally, a crash is the worst outcome for two defectors. One can imagine a large group of cooperators can easily work in the environment, while a group of defectors will result in all robots clumped together, or different groups of robots clumped together in different areas of the environment.

The outcome of each 2-player game can be implicitly observed from the movements of individuals. A defector heading toward a cooperator can continue straight a way, while cooperators need to swerve, and two defectors bumping into each other will get stuck for a while, until they can both completely turn around and continue in different directions. This shows how the fitness definition in Eq. 1 can reflect the reward/punishment of each game.

The third behavior which is implemented on robots is an *escape* behavior which is activated when robots get stuck due to unknown reasons for a long time. This can happen due to errors in sensor reading, crowded passways, etc. In such situations, robots start to turn randomly and move back and forth, until they can continue with the *random walk* behavior.

For more information about implementation of the behaviors see [11, 12].

4 Experiments

In this section, groups of cooperating and defecting robots are used to evaluate each of these behaviors in two different types of regular and small-world environments.

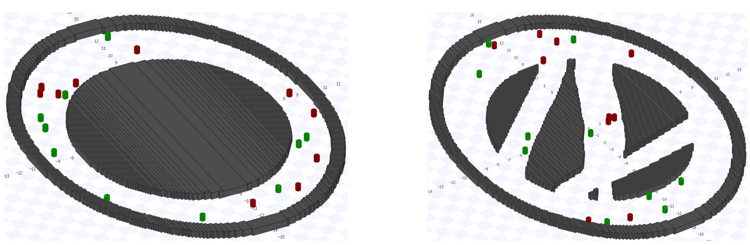
4.1 Robotic Platform and Simulation Environment

The robots used for the proposed robotic platform should be able to do basic tasks such as moving in different directions with a reasonable speed and detection of obstacles. Robots should also be able to interact with other near by robots following their pre-defined behaviors (i.e., either cooperation or defection), and avoid getting stuck in the environment due to unknown reasons.

Therefore, this work uses the *Turtlebot*[1] robot. This robot is equipped with strong wheels and encoders, a Kinect[2] camera and a laptop. This robot can be easily programmed by ROS[3], which allows us to implement a specific code easily on multiple robots. Besides, the exact same code can be used in simulation environment. For more sophisticated details about Turtlebot features and its comparison with a limited-resource robot, refer to [1].

For the experiments reported in this paper, identical Turtlebot robots are defined in the Stage simulator [19]. This simulator is designed for simulation of multi-agent autonomous systems, and it allows us to modify the environment maps easily using a Portable Gray Map (PGM) format file.

Every experiment is carried out with 20 robots with pre-defined behaviors, starting from a random initial position in the environments shown in Figure 3. Each experiment is executed two times for a duration of 5 minutes each.



(a) Regular Environment (b) Small World Environment

Figure 3: The environment map used for experiments. (a) a regular map in which robots are surrounded by their immediate neighbors and can hardly move to other neighborhoods. (b) a small-world map in which robots have shortcuts for moving to many different locations.

In all experiments, the diameter of the environment is $25m$. The laser scanner of the robots detects the range $0 - 4m$, its field of view is 170 degrees with 340 rays. The robot has the dimensions $35cm \times 35cm \times 45cm$, which is identical to a real Turtlebot.

4.2 Results

Seven main experiments are defined for evaluating the Cooperation and Defection in a social structure (Table 1). These experiments are different in terms of ratio between cooperators and defectors in the multi-robot group (ranging from 5% to 95%).

The results of the experiments are illustrated in Subfigures 4(a) and 4(b). Subfigure 4(a) shows how the average fitness of defectors and cooperators change with respect to the ratio of (number of) cooperators to (number of) defectors. As can be seen in this subfigure, by increasing the ratio of cooperators to defectors,

[1] http://www.turtlebot.com
[2] http://en.wikipedia.org/wiki/Kinect
[3] Robot Operating System http://www.ros.org

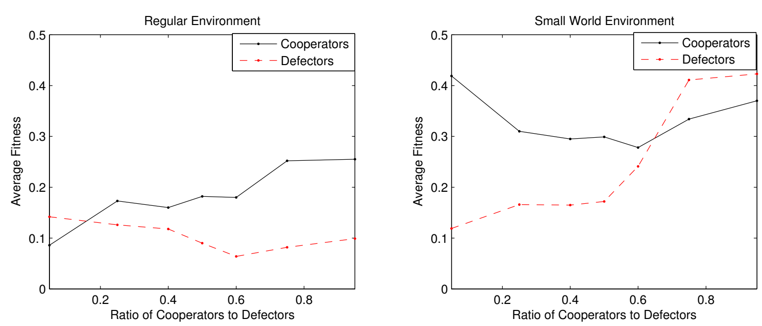
Table 1: Valuation of Cooperation and Defection in different experiments. F_c and F_d denote the average fitness of cooperators and defector, respectively.

Experiment	Number of Cooperators	Number of Defectors	Regular Environment			Small-World Environment		
			F_c	F_d	F_c/F_d	F_c	F_d	F_c/F_d
Exp. 1	1	19	0.086	0.142	0.6056	0.419	0.119	3.5210
Exp. 2	5	15	0.173	0.126	1.3730	0.310	0.166	1.8675
Exp. 3	8	12	0.160	0.118	1.3559	0.295	0.165	1.7879
Exp. 4	10	10	0.182	0.090	2.0222	0.299	0.172	1.7384
Exp. 5	12	8	0.180	0.064	2.8125	0.278	0.241	1.1535
Exp. 6	15	5	0.252	0.082	3.0732	0.334	0.411	0.8127
Exp. 7	19	9	0.255	0.099	2.5758	0.370	0.423	0.8747

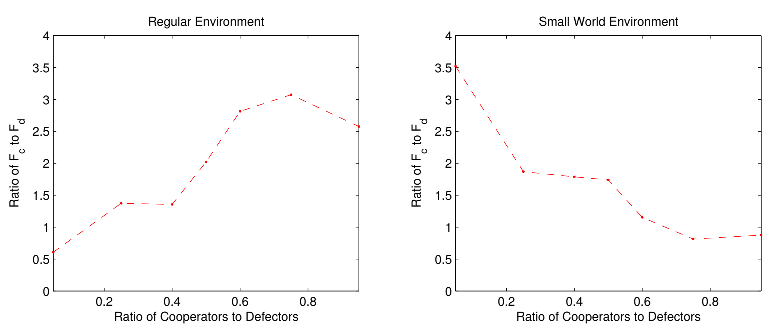
the fitness of defectors F_d decreases compared to fitness of cooperators F_c in a regular environment. In contrast, in the small-world network the reverse behavior is observed, and defectors can even get a higher fitness if they are in minority compared to cooperators.

Given that the average fitness represents the average speed of the robots, in a regular environment, robots can move with an average speed of $15cm/s$ and this increases to about $25cm/s$ in a small-world environment.

The ratio of F_c to F_d is depicted in Subfigure 4(b). This subfigure, clearly shows the reverse trend between regular environment and small-world environment.



(a) Average fitness of cooperators and defectors



(b) Ratio of fitness of cooperators to defectors

Figure 4: A comparison between fitness of cooperators and defectors in different experiments.

Based on the presented results in this subsection, in a regular environment the value of cooperation compared to defection is increased by an increase in number of cooperators. In contrast, in a small-world environment, the value of cooperation compared to defection is decreased by an increase in number of cooperators. To sum up, in small-world networks the individuals whose behavior is in minority get the highest payoff, while in regular networks the individuals in majority can get a higher payoff.

Another interesting result from Figure 4 is that the macroscopic fitness of the group (i.e. the sum of fitness of all individuals) is proportional to number of cooperators; the more cooperators exist in the group the faster robots can traverse the environment, and higher payoff they get.

5 Discussion

The results provided in previous section clearly show that the proposed multi-robot framework is capable of studying the simple behaviors in a social network. For instance, a major difference between observations on a regular network and small-world network that was already reported elsewhere [20] is confirmed through our experiments. Furthermore, the effect of population ratio on the fitness levels which is a known concept for the Predator-Prey scenarios [2] is also confirmed by this work.

One example of unexpected behaviors observed during the experiments, is the chaotic behavior in dense clusters of robots. In such situations, robots can hardly determine a fixed opponent robot to play the game with, and many unexpected crashes take place. Our analysis revealed that cooperators behave like defectors in such chaotic situations, and therefore decreases the fitness of every individual in that cluster. Such dense clusters are seen more often in regular environments than small-world ones, as in the latter one there are usually shortcuts for robots to escape from such dense clusters. This can be considered as a main reason for the reverse trends between regular and small-world environments as shown Figure 4.

The discussed research opens several interesting research avenues. For instance, assume that following the "survival of the fittest rule" [7], we let the robots learn from the behavior of the fittest in the group. As explained in this paper the defectors in minority can be the fittest in a small-world environment. As other individuals start to learn this behavior, their fitness will decrease. Given that the group should eventually agree on a fixed strategy [16], studying which strategy the group agrees on can be very interesting. Furthermore the feasible ways to influence the behaviors [6] can be studied using the proposed framework. These two clearly explain the next steps in our study.

6 Conclusion

Due to complexities of the social ties in a network of social actors, valuation of social behaviors is a very difficult task. The effects of physical environment and interaction dynamics on such behaviors can make it almost impossible to use theoretical approaches and numerical simulations to analyze evolution of behaviors. In this paper a behavioral robotic approach was proposed which maintains the formal game theoretical definitions, and is still feasible for implementation on a large group of robots. The experimental results on two different environment structures with various population distributions for cooperating and defecting agents verified that the proposed framework generates a realistic valuation for behaviors and can be used for further studies on social behaviors. For instance, the results showed that defecting agents which are in the minority compared to cooperating agents can achieve a high fitness in a small-world setting, but this is not the case in regular networks due to emerged chaotic behaviors.

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