Applying Social Network Analysis to Agent-Based Models: A Case Study of Task Allocation in Swarm Robotics Inspired by Ant Foraging Behavior

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Abstract

Social network analysis and agent-based modeling are two approaches used to study biological and artificial multi-agent systems. However, so far there is little work integrating these two approaches. Here we present a first step toward integration. We developed a novel approach that allows the creation of a social network on the basis of measures of interactions in an agent-based model for purposes of social network analysis. We illustrate this approach by applying it to a minimalist case study in swarm robotics loosely inspired by ant foraging behavior. For simplicity, we measured a network's inter-agent connection weights as the total number of interactions between mobile agents. This measure allowed us to construct weighted directed networks from the simulation results. We then applied standard methods from social network analysis, specifically focusing on node centralities, to find out which are the most influential nodes in the network. This revealed that task allocation emerges and induces two classes of agents, namely foragers and loafers, and that their relative frequency depends on food availability. This finding is consistent with the behavioral analysis, thereby showing the compatibility of these two approaches.

Introduction

Social network analysis (SNA) has been widely used in the study of biological multi-agent systems (Krause et al., 2015). In recent years, there has been an increasing interest in analyzing animal social networks (Scott and Carrington, 2014). For example, there are studies in social networks of spider monkeys (Ramos-Fernández et al., 2009), crows (Rutz et al., 2012) and social insects (Charbonneau et al., 2013). Similarly, agent-based modeling (ABM) has been applied to the same area. Ramos-Fernández et al. (2006) studied the emergence of animal social structure using agent-based models. Guo and Wilensky (2016), researchers in Alife, have demonstrated the utility of agent-based models of social insects as powerful tools to understand complex system principles. Moreover, Wang et al. (2019) studied collective behavior of bacteria, which use signaling systems known as quorum-sensing (QS) to communicate and cooperate. They used an agent-based modeling approach to understand the emergence of complex QS architectures and functions.

On the other hand, there are few studies using these two approaches (SNA and ABM) in combination in artificial multi-agent systems (MAS), particularly, in swarm robotics. Swarm robotics is a recent approach in the field of artificial swarm intelligence to study the coordination of multi-robot systems (MRS) without central control inspired on swarms observed in nature, such as those of social insects. Collective behavior emerges from robot-robot and robot-environment interactions (Tan and Zheng, 2013). There is a strong potential found in mimicking social insect behavior because this is highly convenient for solving complex coordination tasks (Alers et al., 2014). For example, ant foraging behavior induces task allocation as an emergent property, which is suitable for swarm robotics (Labella et al., 2006).

In this study, we are interested in applying social network analysis to agent-based modeling. There are previous studies that successfully combined SNA and ABM (Fontana and Terna, 2015) or SNA and MAS (Ma et al., 2009; Grant, 2009). For a better understanding, we have developed a taxonomy of social interaction models based on the approach of Powers et al. (2018), as shown in Figure 1.

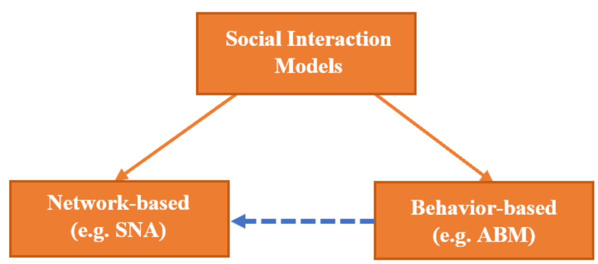


Figure 1: A taxonomy of social interaction models. We have two classes of social interaction models: network-based and behavior-based. Social network analysis (SNA) is an instance of network-based model and agent-based modeling (ABM) is an instance of behavior-based model. We propose there should be a bridge (dashed blue arrow) from behavior-based to network-based models to have a complete perspective of the network dynamics in a complex system in order to get new insights on their emerging properties. That is, moving from agent-based modeling to social network analysis.

Figure 1 shows our proposed taxonomy where we consider there should be a bridge from behavior-based (e.g. ABM) to network-based (e.g. SNA) models to have a complete perspective of the network dynamics in a complex system in order to get new insights on its emerging properties. Thus, our representation of moving from ABM to SNA.

We found that this approach (from ABM to SNA) has not been exploited in foraging and task allocation in swarm robotics. However, there are previous papers using either one of these two approaches (ABM or SNA). Iba (2013), developed agent-based modeling and simulations with swarms; Palestra et al. (2017), modeled and simulated rescue robots using the swarm robotics approach; Koval et al. (2009), introduced a social network to a swarm robotics system in order to improve accuracy in automatic target recognition.

The main goal of this study is to apply our proposed approach, from agent-based modeling to social network analysis, to a case study in swarm robotics inspired by ant foraging behavior to show task allocation as an emergent property of the complex system.

The case of ant foraging behavior in swarm robotics

Task allocation, in social insects, refers to the processes by which a task is carried out by each member of the colony. As examples, we have foraging and brood care. Additionally, these processes adapt to changing conditions (Gordon, 2016). In this paper, we are interested in task allocation as an emergent property of ant foraging behavior.

The main features of ant foraging behavior can be summarized as follows (Labella et al., 2006):

- The ant explores the environment in random displacements until it finds food. There are three cases of how to take it to the nest: (i) the ant pulls it, if it is not too heavy, (ii) the ant cuts it, (iii) the ant uses long or short recruitment (as a result of spreading pheromone trail).
- In individual or collective retrieval, food is directly pulled to the nest.
- When a forager returns to the nest, it unloads food by mouth-to-mouth contact into the *crops* (a pouch located just upstream of their stomachs) of other ants (Greenwald et al., 2018).
- After retrieving food, the ant goes straight back to the location where it found food.

Deneubourg et al. (1987) modeled an ant of the species *Pachycondyla apicalis* as an agent. Each agent has a probability P_l of leaving the nest, that varies depending on prior successes or failures. That is, when an ant retrieves food, its P_l increases by a constant Δ. Conversely, when an ant spends a lot of time without retrieving food, its P_l decreases by a constant Δ. P_l is bounded in the range [P_{min}, P_{max}]. They showed, by means of numerical simulations, that this model can explain task allocation and adaptation to the environment in ants (Labella et al., 2006).

The Variable Delta Rule algorithm (VDR) was based on Deneubourg et al.'s model. The main change was to multiply Δ by the number of consecutive successes or failures when increasing or decreasing the probability of leaving the nest, P_l, to carry out experiments in less time (Labella, 2003; Labella et al., 2006). This simple algorithm might be well suited for use in the context of swarm robotics.

Foraging, in test application for multi-robot systems (MRS), refers to searching for objects and taking them to a place called "nest" (Labella, 2003).

A swarm of interacting robots produces emergent behaviors. We can analyze the local interactions that allow the process of self-organization in these robots using social network analysis. Social network analysis studies the structural properties of groups or individuals in a network. It considers the effect of the interconnections on each other (Srivastava et al., 2014).

We developed an agent-based model based on the Variable Delta Rule algorithm to simulate a swarm of robots inspired by ant foraging behavior. Furthermore, for simplicity we focused on one of the main traits of *Pachycondyla apicalis* ants, that is hunting alone, consequently, there is no need of pheromone trails (Monmarché et al., 2000). Therefore, we modeled the case in which each forager takes only a unit of food when having a successful food retrieval without using pheromone trails. Then, we applied social network analysis to show task allocation as an emergent property of this model.

Methods

In this section, we present the methodology and tools that we used to implement, simulate and analyze the agent-based model of swarm robotics.

Variable Delta Rule Algorithm

We implemented the Variable Delta Rule algorithm (Labella, 2003; Labella et al., 2006). It consists in the following rules: each time the mobile agent has a success in food retrieval, the number of successes is increased and multiplied by Δ, then it is added to its P_l. Conversely, if the mobile agent has a failure in food retrieval, the number of failures is increased and multiplied by Δ, then it is subtracted from its P_l. Therefore, each mobile agent's probability of leaving the nest, P_l, is determined by the number of consecutive successful or failed food retrieval events. Note that P_l is bounded in the range [P_{min}, P_{max}]. This is shown in Algorithm 1.

Algorithm 1 Variable Delta Rule

```
Initialization:
    successes ← 0
    failures ← 0
    P_l ← Initial value

if food is retrieved then
    successes ← successes + 1
    failures ← 0
    P_l ← P_l + (successes * Δ)
    if P_l > P_max then
        P_l ← P_max
    end if
else if timeout then
    failures ← failures + 1
    successes ← 0
    P_l ← P_l - (failures * Δ)
    if P_l < P_min then
        P_l ← P_min
```

Agent-based model (ABM) of swarm robotics

Environment. The simulated environment is a bounded two-dimensional grid (when a mobile agent reaches an edge it rotates 180 degrees and continues moving) and has a size of 91 x 91 units, with a unique nest located at the center (cluster of brown patches). A unit of the grid is represented by a patch of 5 x 5 pixels. A unit of food is represented by a unit of the grid located in a food source.

A fixed value in the range [0, 200] is assigned to each unit of the grid as follows: the distance between the focal unit of the grid and the center of the nest is calculated, then it is subtracted from 200 to obtain its "nest scent" value. This value is greater as the focal unit of the grid is closer to the nest. This approach is used by mobile agents to find their way back to the nest, it is known as following "nest scent" and it is described as follows: before each step forward when coming back directly to the nest, the mobile agent is going to head toward the greatest value of "nest scent" that is ahead of it and between the angles -45, 0 or 45. This is repeated until reaching the nest (Wilensky, 1997).

On the grid, food sources are clusters of units of food that are established in a fixed position and have a variable size between small (9 units of food), medium (45 units of food) or large (109 units of food). We have three food sources identified with the following colors, from the closest to the furthest from the nest: magenta, lime and turquoise. Figure 2 shows the distribution and different sizes for food sources in the environment. The environment is dynamic. A food source decreases by one unit of food each time a mobile agent has a successful food retrieval.

a) b) c)

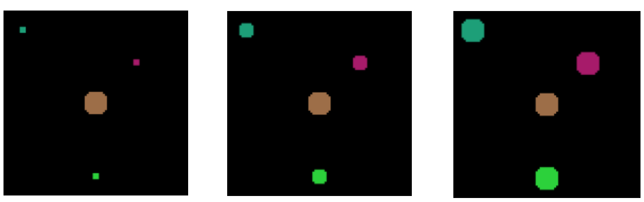


Figure 2: The simulated environments with different sized food clusters: a) Small (9 units of food for each food source), b) Medium (45 units of food for each food source), c) Large (109 units of food for each food source). The nest is in the center of the environment (cluster of brown patches). There are three available food sources, the color of each one indicates the distance to the nest, from the closest to the furthest we have: magenta, lime and turquoise.

Mobile Agents. We consider six mobile agents with initial positions in the center of the nest. Each mobile agent represents a robot. Movements, behaviors and interactions of mobile agents are described as follows:

Movements. Mobile agents have two classes of movements, these are described as follows:

- **Foraging movement:** When a mobile agent is out of the nest, it moves around the environment by random displacements to right and left each time-step, while considering not to take an occupied unit of the grid where another mobile agent is, as an obstacle avoidance mechanism. A displacement has a maximum turning angle of ± 40 degrees (Wilensky, 1997).
- **Nest seeking movement:** When a mobile agent is returning to the nest, it moves by displacements following the "nest scent" in each time-step. That is, it moves towards the next unit of the grid that has the greatest value of "nest scent" until reaching the nest, while considering not to take an occupied unit of the grid where another mobile agent is, to avoid obstacles.

Behaviors. Each mobile agent assumes one of the following behaviors per time-step depending on its own parameters and environment conditions (Labella et al., 2006):

- **Rest:** Stays in the nest.
- **Search for food:** Explores the environment while checking if there is a unit of food in the path. If there is one, the mobile agent takes it and returns to the nest with food (its number of successes is increased). If there is not one, the mobile agent keeps randomly moving around until a timeout occurs and it returns to the nest without food (its number of failures is increased).
- **Return to nest:** Finds the way back to the nest following the "nest scent" (Wilensky, 1997). It returns to the nest if a unit of food was successfully retrieved or a timeout occurs.
- **Feed:** Transfers food to all the mobile agents in the nest, when arriving to it after a successful food retrieval. Its number of successes is increased by one, therefore its probability of leaving the nest is going to be higher when updating it.

Furthermore, the mobile agents change their color to identify the performed behavior, as shown in Table 1.

Behavior	Color
Rest	Blue
Search for food	Red
Return to nest (with food)	Yellow
Return to nest (without food)	Violet
Feed	Orange

Table 1: Colors representing the behavior of each agent.

Interactions.

- **Agent - Agent (among mobile agents):** When a mobile agent arrives to the nest after retrieving a unit of food, there is an interaction between that mobile agent (emitter) and all the mobile agents in the nest (receivers), which represents food transfer. When a mobile agent is the emitter, its corresponding interaction variables (each one corresponds to an emitter-receiver interaction) increase by one. This is prompted by the forager ant's interactions with the rest of the colony to feed them. Figure 4 shows an example of interaction among mobile agents.

Figure 4: Interaction between mobile agents. The orange-colored mobile agent (emitter) returned to the nest after retrieving a unit of food, when it arrives to the nest it interacts with all the blue-colored mobile agents (receivers) that are on the cluster of brown patches. This interaction represents food transfer (white arrow) from emitter to receivers and is loosely inspired by a forager ant feeding the rest of the colony in the nest.

• **Agent - Food Source (among mobile agents and food source clusters):** When a mobile agent finds and retrieves a unit of food, there is an interaction between that mobile agent and the retrieved unit of food from a food source, this is inspired by the forager ant's interactions with a food source. Each time a unit of food is retrieved from a food source, the number of units of food of that food source is decreased and the retrieved unit of food changes to color black to represent it was taken. Figure 5 shows an example of interaction among a mobile agent and a food source.

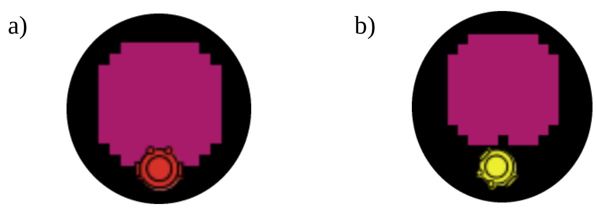


Figure 5: Interaction between a mobile agent and a food source. a) When a red-colored mobile agent finds out a unit of food, it interacts with the food source and b) it changes its color to yellow. The retrieved unit of food changes to color black to represent it was taken.

Experiments

The simulation-based experiments consisted in introducing a swarm of six mobile agents and three food sources (clusters of magenta, lime and turquoise patches), which we varied from small sizes (9 units of food for each food source cluster), medium sizes (45 units of food for each food source cluster) and large sizes (109 units of food for each food source cluster) to show task allocation under changing conditions of the environment. We created 30 instances per food sources size, i.e. 90 simulations in total. Each simulation lasted 2400 time-steps. The model was initialized with the following parameters (Labella, 2003): The search timeout was fixed to 228 units of time, Δ was set to 0.005, P_{min} to 0.0015, P_{max} to 0.05 and P_{init} to 0.033. Figure 6 shows a representative simulation of the agent-based model of swarm robotics and its components.

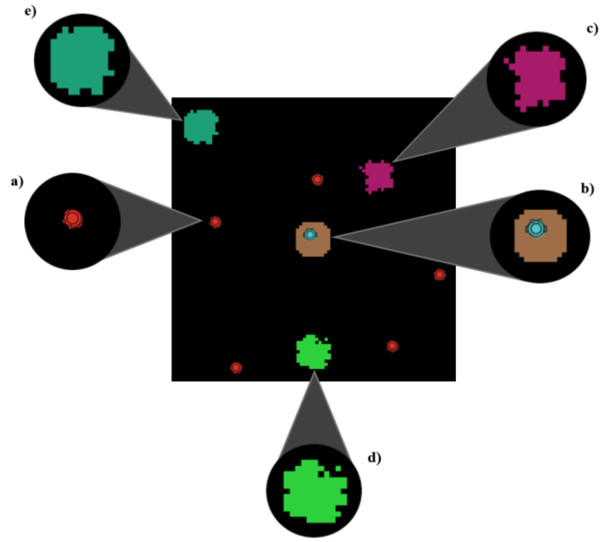


Figure 6: Screenshot of the agent-based model of swarm robotics after 2400 time-steps. a) Red-colored mobile agents are searching for food and b) blue-colored mobile agents are resting in the nest (cluster of brown patches). There are three food sources, from closest to furthest to the nest: c) magenta, d) lime and e) turquoise.

Social network analysis (SNA)

We followed the proposal by Wasserman and Faust (1994), who used network graphs to represent agent structures and network measures such as strength and centrality, to determine the particular role of individuals in the network's structure. We propose to represent mobile agents and their interactions in each simulation as a weighted directed network and focus on outdegree and weighted outdegree centralities to identify the induced classes, as a result of task allocation: foragers and loafers.

We constructed ninety weighted directed networks, from the 90 simulations, i.e. 30 simulations per food sources size (small, medium and large) as described in the Methods. We added a directed edge between two nodes (source and target) to represent whenever one of the two mobile agents (emitter) interacted with another one in the nest (receiver) to represent food transfer, this is inspired by the forager ants' interactions with the rest of the colony to feed them. Weights were assigned according to the number of interactions between the two mobile agents. Nodes were labeled with the six mobile agents' identifiers, from 0 to 5.

Measures were computed for each weighted directed network. We focused on outdegree and weighted outdegree centralities. Degree centrality shows the quality of a network node's interconnectedness by the number of direct contacts (Landherr et al., 2010). The outdegree is the number of ties that a node directs to others, it is interpreted as a quantity of information that is spread from one node to other (by outgoing edge). A high value is interpreted as sociability (Mansur et al., 2016). The centrality of nodes allows us to identify the most important or central nodes in a network.

Thus, outdegree centrality is a measure of the importance of a node, based on its number of ties. It is interpreted as the involvement of a node in the network. Weighted outdegree centrality is a measure of the importance of a node, based on its strength in terms of the total weight of their connections. It is interpreted as strength of collaborative ties (Opsahl et al., 2010). To calculate node strength, we have the following equation:

$$s_i = \sum_{j}^{N} w_{ij} \tag{1}$$

where w is the weighted adjacency matrix and w_{ij} represents the weight of the tie, it is greater than 0 if the node i is connected to node j (Opsahl et al., 2010).

Outdegree centrality can lead us to identify the mobile agents who are the most interconnected to others (i.e. more ties), whereas weighted outdegree centrality can lead us to identify the mobile agents who have the greatest number of interactions (i.e. wider edges) with the rest. Hence, we need both centrality measures to identify the expected induced classes, as a result of task allocation: foragers and loafers. Foragers' task consists in searching and retrieving food to feed the rest of the mobile agents; loafers' task consists in staying in the nest. Thus, foragers must be the most interconnected to the rest (i.e. having more ties) and with the greatest number of interactions (i.e. having wider edges). In the shown networks, node size refers to the value of outdegree or weighted outdegree centralities.

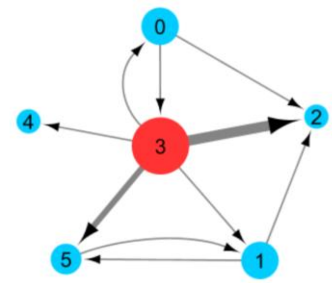
According to Labella's (2003) experimental results with *MindS-bots* (swarm of robots), he found that the distribution of probability of leaving the nest had two peaks and the boundary between the two groups was around 0.025, therefore there were two groups of *MindS-bots*: foragers ($P_l \geq 0.025$) and loafers ($P_l < 0.025$). As described in the Experiments, our model was initialized under Labella's (2003) experimental parameters, thus, we compared the results with the second parameter to identify foragers and loafers: mean probability of leaving the nest (mean P_l). Therefore, those mobile agents with mean $P_l \geq 0.025$ are likely to be foragers (red-colored nodes) and those with mean $P_l < 0.025$ are likely to be loafers (blue-colored nodes).

Results

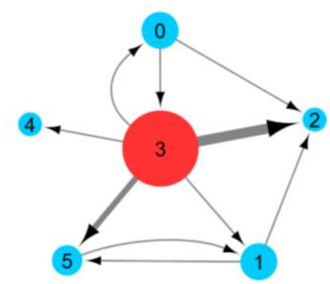
First, we show the results for three representative simulations (each one with a different food sources size). Then, we show in summary the results for the 90 simulations.

Simulation 1 - Small food sources size

Figure 7 shows the weighted directed network obtained with the results of simulation 1. The mean outdegree centrality of this network was 1.83, that indicates there were few nodes that were the most interconnected to others, in this case, only node 3 had ties to all the other nodes. The mean weighted outdegree centrality was 2.17, that indicates there were few interactions between mobile agents. There were two edges with high weight values, those were (3,2) and (3,5), which represented the greatest number of interactions between the mobile agents. Node 3 had the greatest number of ties and wider edges, moreover, it has a $P_l > 0.025$, therefore we interpreted it as a forager. The mean probability of leaving the nest of all nodes was 0.021, which was less than 0.025, so we expected more loafers than foragers. Likely agents to be foragers by P_l were represented by red-colored nodes and likely agents to be loafers by P_l were represented by blue-colored nodes. After analyzing the results, we got 1 forager (node 3) and 5 loafers (nodes 0, 1, 2, 4, 5).



(a) Social network 1 with nodes sized by their outdegree centrality



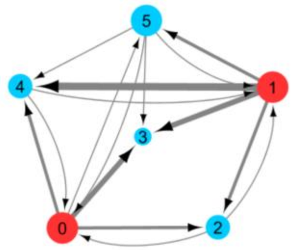
(b) Social network 1 with nodes sized by their weighted outdegree centrality

Figure 7: Graphs of social network 1 (the size of food sources is small) between six mobile agents where node sizes are reflecting: (a) Outdegree centrality, (b) Weighted outdegree centrality. Edge widths are reflecting the number of interactions between mobile agents. Node colors represent the probability of leaving the nest: if $P_l \geq 0.025$ the node is red, therefore, it is likely to be a forager and if $P_l < 0.025$ the node is blue, therefore, it is likely to be a loafer. As it can be seen, node color and size are consistent with each other, that means bigger nodes and probability to be a forager coincide; similarly, smaller nodes and probability to be a loafer also coincide. Therefore, both approaches obtain same results (in this case, 1 forager and 5 loafers).

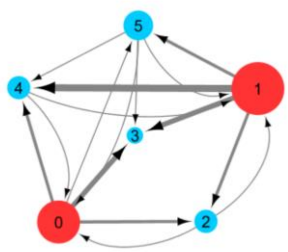
Simulation 2 - Medium food sources size

Figure 8 shows the weighted directed network obtained with the results of simulation 2. The mean outdegree centrality of this network was 2.67, that indicates there was a moderate number of nodes that were the most interconnected to others, more than in Simulation 1. The mean weighted outdegree centrality was 4.5, that indicates there was a greater number of interactions between mobile agents than in Simulation 1.

There were seven edges with high weight values, those were (1,5), (1,4), (1,3), (1,2), (0,4), (0,3) and (0,2) which represented the greatest number of interactions between agents. Nodes 0 and 1 had the greatest number of ties and wider edges, moreover, their P_l > 0.025, therefore we interpreted them as foragers. The mean probability of leaving the nest of all nodes was 0.022, which was less than 0.025, so we expected more loafers than foragers. After analyzing the results, we got 2 foragers (nodes 0, 1) and 4 loafers (nodes 2, 3, 4, 5).



(a) Social network 2 with nodes sized by their outdegree centrality

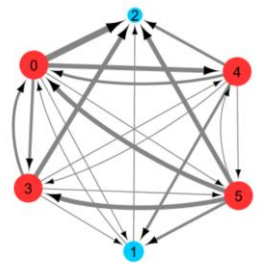


(b) Social network 2 with nodes sized by their weighted outdegree centrality

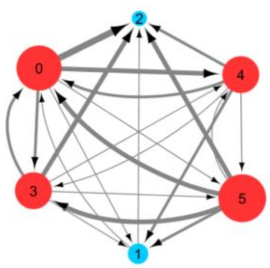
Figure 8: Graphs of social network 2 (the size of food sources is medium) between six mobile agents where node sizes are reflecting: (a) Outdegree centrality, (b) Weighted outdegree centrality. Edge widths are reflecting the number of interactions between mobile agents. Node colors represent the probability of leaving the nest: if $P_l \geq 0.025$ the node is red; therefore, it is likely to be a forager and if $P_l < 0.025$ the node is blue; therefore, it is likely to be a loafer. As it can be seen, node color and size are consistent with each other, that means bigger nodes and probability to be a forager coincide; similarly, smaller nodes and probability to be a loafer also coincide. Therefore, both approaches obtain same results (in this case, 2 foragers and 4 loafers).

Simulation 3 - Large food sources size

Figure 9 shows the weighted directed network obtained with the results of simulation 3. The mean outdegree centrality of this network was 3.6, that indicates there were many nodes that were the most interconnected to others, more than in Simulations 1 and 2. The mean weighted outdegree centrality was 6.83, that indicates there was a greater number of interactions between mobile agents than in Simulations 1 and 2. There were many edges with high weight values, due to high food availability. Nodes 0, 3, 4 and 5 had the greatest number of ties and wider edges, moreover, their P_l > 0.025, therefore we interpreted them as foragers. The mean probability of leaving the nest of all nodes was 0.029, which was greater than 0.025, so we expected more foragers than loafers. After analyzing the results, we got 4 foragers (nodes 0, 3, 4, 5) and 2 loafers (nodes 1, 2).



(a) Social network 3 with nodes sized by their outdegree centrality



(b) Social network 3 with nodes sized by their weighted outdegree centrality

Figure 9: Graphs of social network 3 (the size of food sources is large) between six mobile agents where node sizes are reflecting: (a) Outdegree centrality, (b) Weighted outdegree centrality. Edge widths are reflecting the number of interactions between mobile agents. Node colors represent the probability of leaving the nest: if $P_l \geq 0.025$ the node is red; therefore, it is likely to be a forager and if $P_l < 0.025$ the node is blue; therefore, it is likely to be a loafer. As it can be seen, node color and size are consistent with each other, that means bigger nodes and probability to be a forager coincide; similarly, smaller nodes and probability to be a loafer also coincide. Therefore, both approaches obtain same results (in this case, 4 foragers and 2 loafers).

Summary of results

The results of the social network analysis applied to the 90 weighted directed networks obtained from the simulation experiments are summarized in Table 2. It reports the mean and standard deviation of number of foragers and loafers.

Figure 10 shows the results of mean and standard deviation of probability of leaving the nest of the six mobile agents in the 30 experiments per food sources size (i.e. 90 experiments in total).

Contrasting the results of Table 2 and Figure 10, we can see that the social network analysis results confirmed the expectations of number of loafers and foragers obtained by the mean probability of leaving the nest varying the food sources size. Hence, the results proved task allocation among mobile agents as an emergent property of this model, inducing two classes: foragers and loafers. The number of foragers and loafers was adapted to the environment conditions (in this case, food availability).

Food Sources Size	Food availability	Number of Foragers	Number of Loafers
Small	Low	1.1 ± 0.3051	4.9 ± 0.3051
Medium	Medium	3.07 ± 0.7397	2.93 ± 0.7397
Large	High	4.77 ± 0.4302	1.23 ± 0.4302

Table 2: Mean and standard deviation of number of foragers and loafers calculated over 30 simulations per food sources size (i.e. 90 simulations in total) by applying social network analysis to the obtained weighted directed networks. The low values of standard deviation indicate that the behavior of the model was consistent across simulations.

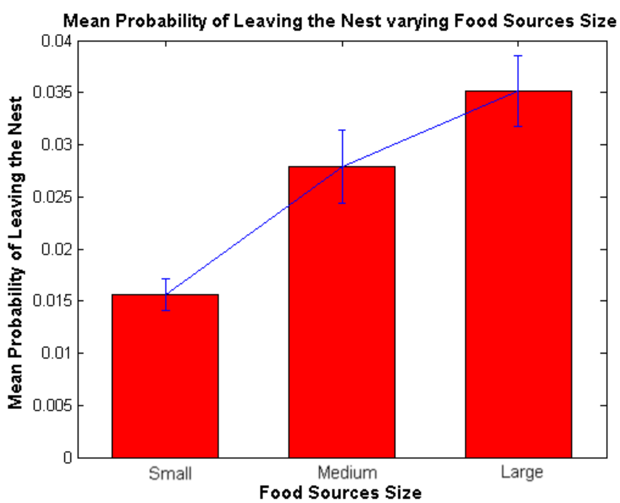


Figure 10: Mean and standard deviation of probability of leaving the nest while varying food sources size. The low standard deviation indicates that the behavior of the model was consistent across simulation experiments. These results show that with a low availability of food (small sized food sources) the mean $P_l < 0.025$, therefore, we expected more loafers than foragers; with a medium availability of food (medium sized food sources) the mean P_l is a little above 0.025, therefore, we expected similar number of loafers and foragers; with a high availability of food (large sized food sources) the mean $P_l > 0.025$, therefore, we expected more foragers than loafers.

Emergent property - Task allocation

In all simulations we observed that task allocation emerged and induced two classes: foragers and loafers. There were more loafers than foragers with low food availability (i.e. small sized food sources); there was similar number of loafers and foragers with medium food availability (i.e. medium sized food sources); and there were more foragers than loafers with high food availability (i.e. large sized food sources).

Discussion

As we have seen, moving from agent-based modeling (ABM) to social network analysis (SNA) lead us to a better understanding of the complex system by studying its emergent properties. In our agent-based model of swarm robotics we have shown that task allocation emerges and induces the creation of two classes: foragers and loafers. Furthermore, one of our main results was that the number of foragers and loafers changed with the conditions of the environment, as in real ant colonies. It means, task allocation changes as conditions vary (Gordon, 1999). Our model highlights that when more food is available, more foragers appear, and vice versa, as we observed in the weighted directed networks that we created for each simulation results. Thus, we conclude task allocation implies an adaptive and self-organized process (Labella, 2003).

A distinctive property revealed by the social network analysis was that the nodes with the greatest outdegree centralities were the most interconnected with the others (i.e. more ties) and those with the greatest weighted outdegree centralities had wider edges, therefore those nodes which were bigger in both graphs were the most interconnected mobile agents (i.e. having more ties) with the greatest number of interactions (i.e. having wider edges), hence we can call them, the "influentials" in the colony. These are the foragers.

Conclusions and Future Work

To summarize, we presented and analyzed our agent-based model of swarm robotics using social network analysis to show that it exhibits task allocation as an emergent property due to the Variable Delta Rule algorithm (Labella, 2003; Labella et al., 2006), which was inspired by ant foraging behavior. In future work, we are going to explore more complicated scenarios, for example, considering cheaters, those social insects that exploit the benefits of biological cooperation without contributing to them (Dobata and Tsuji, 2009). Moreover, this can be extended by using social network analysis to develop agent-based models, that is, moving from social networks to multi-agent systems in order to establish the measures of those networks and then design agent's behaviors that will reach those measures. This could potentially be used in order to run game theoretic (network) models in an agent-based modeling framework.

References

Alers, S., Tuyls, K., Ranjbar-Sahraei, B., Claes, D. and Weiss, G. (2014). Insect-Inspired Robot Coordination: Foraging and Coverage. In Sayama, H., Rieffel, J., Risi, S., Doursat, R. and Lipson, H., editors, *Proceedings of the Fourteenth International Conference on the Synthesis and Simulation of Living Systems (ALIFE 14)*, pages 761-768. MIT Press, Cambridge, MA.

Charbonneau, D., Blonder, B. and Dornhaus, A. (2013). Social Insects: A Model System for Network Dynamics. In: Holme P. and Saramäki J., editors, *Temporal Networks*, pages 217-244. Springer, Berlin.

Deneubourg, J.-L., Goss, S., Pasteels, J. M., Fresneau, D. and Lachaud, J.-P. (1987). Self-organization mechanisms in ant societies (II): Learning in foraging and division of labor. In Pasteels, J. and Deneubourg, J.-L., editors, *From Individual to Collective Behavior in Social Insects*, Experientia Supplementum, 54:177-196. Birkhäuser Verlag, Basel, Switzerland.

Dobata, S. and Tsuji, K. (2009). A cheater lineage in a social insect: Implications for the evolution of cooperation in the wild. *Communicative & Integrative Biology*, *2*(2):67–70.

Fontana, M. and Terna, P. (2015). From Agent-Based Models to Network Analysis (and Return): The Policy-Making Perspective. *Journal on Policy and Complex Systems*, 2(1):77-92.

Gordon, D. M. (1999). Interaction patterns and task allocation in ant colonies. In Detrain, C., Deneubourg, J.-L., Pasteels, J. M., editors, *Information Processing in Social Insects*, pages 51-67. Birkhäuser Verlag, Basel, Switzerland.

Gordon, D. M. (2016). From division of labor to the collective behavior of social insects. *Behavioral Ecology and Sociobiology*, 70(7):1101–1108.

Grant, T. (2009). Modelling Network-Enabled C2 using Multiple Agents and Social Networks. In Andrighetto, G., Boella, G., Sichman, J. and Verhagen, H., editors, *Proceedings of the Social Networks and Multi-Agent Systems Symposium (SNAMAS-09)*, pages 13-18. The Society for the Study of Artificial Intelligence and the Simulation of Behavior (SSAISB).

Greenwald, E., Baltiansky, L., and Feinerman, O. (2018). Individual crop loads provide local control for collective food intake in ant colonies. *eLife*, 7: e31730. doi:10.7554/eLife.31730

Guo, Y. and Wilensky, U. (2016). Small Bugs, Big Ideas: Teaching Complex Systems Principles Through Agent-Based Models of Social Insects. In Gershenson, C., Froese, T., Siqueiros, J. M., Aguilar, W., Izquierdo, E. J. and Sayama, H., editors, *Proceedings of the Artificial Life Conference 2016*, pages 664-665. MIT Press, Cambridge, MA.

Iba, H. (2013). *Agent-Based Modeling and Simulation with Swarm*. Chapman and Hall/CRC, New York.

Koval, M. C., Rubinoff, A. E. S., Maghami, M. and Georgiopoulos, M. (2009). Social Network Analysis for Target Recognition in Swarm Robotics. *AMALTHEA REU program*.

Krause, J., James, R., Franks, D. W. and Croft, D. P. editors (2015). *Animal Social Networks*. Oxford University Press.

Labella, T. H. (2003). *Prey Retrieval by a Swarm of Robots*. Thesis for the Diplôme d'Études Apronfondies (DEA), Institut de Recherches Interdisciplinaires et de Développements en Intelligence Artificielle (IRIDIA), Université Libre de Bruxelles.

Labella, T. H., Dorigo, M., and Deneubourg, J.-L. (2006). Division of Labour in a Group of Robots Inspired by Ants' Foraging Behaviour. *ACM Transactions on Autonomous and Adaptive Systems*, 1(1):4-25.

Landherr, A., Friedl, B. and Heidemann, J. (2010). A Critical Review of Centrality Measures in Social Networks. *Business & Information Systems Engineering*, 2(6):371-385.

Ma, J., Guo, D., Wang, K., Liu, M. and Chen, S. (2009). Colony Evolution in Social Networks Based on Multi-agent System. In Wang, H., Low, K. S., Wei, K. and Sun, J., editors, *Fifth International Conference on Natural Computation* (ICNC), Vol. 4, pages 594-597. IEEE Computer Society.

Mansur, A. B. F., Yusof, N. and Basori, A. H. (2016). The Analysis of Student Collaborative Work Inside Social Learning Network Analysis Based on Degree and Eigenvector Centrality. *International Journal of Electrical and Computer Engineering (IJECE)*, 6(5):2488-2498.

Monmarché, N., Venturini, G. and Slimane, M. (2000). On how *Pachycondyla apicalis* ants suggest a new search algorithm. *Future Generation Computer Systems*, 16(8):937-946.

Opsahl, T., Agneessens, F. and Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, 32(3):245-251.

Palestra, G., Pazienza, A., Ferilli, S., De Carolis, B. and Esposito, F. (2017). RescueRobot: Simulating Complex Robots Behaviors in Emergency Situations. In Anzalone, S., Farinelli, A., Finzi, A. and Mastrogiovanni, F., editors, *Proceedings of the 4th Italian Workshop on Artificial Intelligence and Robotics (AIRO 2017)*, pages 65-69. CEUR Workshop Proceedings.

Powers, S. T., Ekárt, A. and Lewis, P. R. (2018). Co-creating Enduring Institutions for Socio-Technical Systems: The Complementarity of Content-based and Value-based Modelling Approaches. In Ikegami, T., Virgo, N., Witkowski, O., Oka, M. Suzuki, R. and Iizuka, H., editors, *Proceedings of the 2018 Conference on Artificial Life (ALIFE 2018)*, pages 105-106. MIT Press, Cambridge, MA.

Ramos-Fernández, G., Boyer, D. and Gómez, V. P. (2006). A complex social structure with fission–fusion properties can emerge from a simple foraging model. *Behavioral Ecology and Sociobiology*, 60:536-549. doi:10.1007/s00265-006-0197-x

Ramos-Fernández, G., Boyer, D., Aureli, F. and Vick, L. G., (2009). Association networks in spider monkeys (*Ateles geoffroyi*). *Behavioral Ecology and Sociobiology*, 63(7):999-1013.

Rutz, C., Burns, Z. T., James, R., Ismar, S. M. H., Burt, J., Otis, B., Bowen, J. and St Clair, J. J. H. (2012). Automated mapping of social networks in wild birds. *Current Biology*, 22(17):R669-R671. doi:10.1016/j.cub.2012.06.037

Scott, J. and Carrington, P. J. (2014). *The SAGE Handbook of Social Network Analysis*. SAGE Publications Ltd, London.

Srivastava, A., Anuradha and Gupta, D. J. (2014). Social Network Analysis: Hardly Easy. In *Proceedings of the 2014 International Conference on Reliability, Optimization and Information Technology (ICROIT)*, pages 128-135. IEEE.

Tan, Y. and Zheng, Z. (2013). Research Advance in Swarm Robotics. *Defence Technology*, 9(1):18-39.

Wang, Y., Rattray, J. B., Thomas, S. A., Gurney, J. and Brown, S. P. (2019). In *silico* bacteria evolve robust cooperation via complex quorum-sensing strategies. *bioRxiv* 598508. doi:10.1101/598508

Wasserman, S. and Faust, K. (1994). *Social network analysis: Methods and applications (Vol. 8)*. Cambridge University Press, Cambridge.

Wilensky, U. (1997). NetLogo Ants model. http://ccl.northwestern.edu/netlogo/models/Ants. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL.