Ecologically Inspired Agent Control Model

Maxim D. Peysakhov and William C. Regli *

Department of Computer Science, Drexel University, Philadelphia PA 19104

1 Introduction

In a typical agent based system, a number of mobile agents cooperate to achieve a desired goal. The efficiency of the agent system in reaching the goal, and the completeness of the result depends on the number of agents in the system. Too few agents will not achieve the full potential of parallelism, and will lead to decreased system efficiency. Too many agents can overburden the system with unnecessary overhead, and also can result in significant delays. The task of finding the optimal number of agents required to achieve the desired effect is difficult and problem-specific. In this paper, we propose an ecosystem inspired approach to this problem. Similar to a real ecosystem, our solution will exhibit properties of emergent stability, decentralized control and resilience to possible disturbances. In our work, we propose to solve the technical problem of agent management using an ecological metaphor.

In Section 2 we describe the current state of research in the fields of simulated ecosystems and multi-agent control and stability. In Section 3 introduces the problem of managing the number of agents populating a physical network, as well as explain a proposed solution. Lastly, Section 4 demonstrates the initial experimental results and conclusions.

2 Related Work

2.1 Simulated Ecology

The majority of ecology-inspired systems are used to answer some question about real world ecosystems and its properties. For example, the RAM system has been used to study mosquito control [21]. There are two major approaches to simulating an ecosystem [6]. One is a species-based view of the system, where large classes of individuals interact in the simulation (i.e., modeling the dynamics of interaction of species rather than the interaction of individuals). Evolutionary game theory (e.g., [1] [17] [16]) and dynamical systems (e.g., [9] [14] [13]) are two approaches that often take the species-based view. The second approach is to simulate individuals and their interactions, a bottom up approach to construction of the ecological simulator.

We are most interested in *individual-based* simulations, since they are usually built with software agents. An example of an individual-based approach to

* Academic adviser

ecosystems is a simulated habitat populated with synthetic organisms (agents) [18]. Often such system are used to study the evolution (and co-evolution) of different species and testing their interactions and emergent behavior. Genetic Algorithms [8] and Genetic Programming [10] engines can be used in conjunction with synthetic ecosystems to allow species to evolve over time. Some of the most well known examples of synthetic ecosystems of this type are Evolve 1, 2 and 3 [4] [5] [19], "Artorg world"[3] and LAGER [18].

With this approach, global trends in the behavior of the system may *emerge* as a result of the low-level interactions of individual agents. The emergent behavior observed in an ecosystem may not be obvious given the individual behaviors of agents.

2.2 Agents System Stability

Service replication An increasing number of researchers are investigating the problems of reliability, robustness, and stability of multi-agent systems *(MAS)*. Most approaches toward improving system robustness revolve around the replication of agents and/or services on the MAS network. This direction has been taken by [7], [12], [15] and several others. Existing approaches focus on the methodology of agent/service replication. For example, in [15], Marin acknowledges that a system designer should decide up-front which agents to replicate and how many copies to make.

Probabilistic models Another approach is the application of probabilistic models to the prediction of agent system stability and robustness. This research assumes some uncertainty in agent behavior or the agent's environment, and proposes mechanisms for estimating, evaluating and hopefully improving stability of agent systems. One of the first researchers to analyze probabilistic survivability in an MAS is Kraus in [11]. In that paper Kraus proposed a probabilistic model of MAS survivability based on two assumptions: (1) Global state of the network is known at all times. (2) The probabilities of host or connection failure are known.

An alternative approach was proposed by Artz, et al. in [2], where agents reason about state of the network and security (insecurity) of their actions.

3 Problem Formulation

3.1 Motivation

In a typical dynamic, ad hoc network, there is limited, variable bandwidth between hosts, and the memory and CPU on each host is constrained. Given this dynamic and resource constrained environment, it is impractical to prescribe any pre-computed solution.

The solution we propose for such networks is to create a system that can control the number of agents dynamically, adapting to the ever-changing environment. In order to work in the context of an agent based system, a control system should be *distributed* and *decentralized*. By distributed, we imply that the system should be able to use the underlying network to parallelize problem solving on multiple hosts. By decentralized, we imply that the system should avoid reliance on a single node, and should allow each agent to act independently. The emergent behavior resulting from the individual localized control decisions ideally will yield an optimal, or sufficiently optimal, solution at the global level.

3.2 Approach

Large ecosystems usually have several attractive qualities (such as dynamic decentralized control, self regulation, no single point of failure, robustness, and stability) that we require for our system. We propose a solution to the problem of determining the number of agents appropriate for a task at hand that is inspired by large ecosystems:

1. Each task in our system will be associated with food.
2. Agents completing a task successfully will collect the food points associated with the completed task.
3. Agents consume food points over time to sustain their existence.
4. Agents that exhaust their supply of food die.
5. Abundance of food can cause a new agent to spawn.

By this analogy, tasks can be thought of as plant life growing at some rate. Agents are associated with herbivore animals that perform tasks, therefore eating all the food provided by successfully completing a task. Upon completion of a task, an agent is forced to migrate to look for more food (tasks to complete). As time passes, agents consume food according to a predefined consumption function, analogous to a metabolic rate of an animal. Agents unable to find enough food (tasks) to sustain their existence over time will exhaust their food resources and will be terminated. Large amounts of food collected by a single agent or accumulated in a single location can force a new agent to spawn at this location. Agents procreate by division similar to a cell mitosis. However, this approach makes it impossible for the system to recover from a state with no agents. We suggest that tasks also should have an ability to spawn a servicing agent whenever a certain threshold of accumulated food supply is reached. This control metaphor allows system to dynamically adjust to the variables in the environment, while avoiding the centralized control.

3.3 Formal Model

The set H denotes the set of producers h where $h \in H$, with the production rate defined by a function $F_h(t)$ for each individual producer h. The set A defines the set of consumers a ($a \in A$), and each consumer has a predefined consumption function $f_a(t)$. The dynamic system of H producers and A consumers is considered to be in an equilibrium state over some period of time from t_1 to t_2, if and only if the amount of food produced during that period of time is equal to the amount of food consumed during that same period of time. This relationship can be expressed as:

$$\sum_{h \in H} \int_{t_1}^{t_2} F_h(t)\, dt = \sum_{a \in A} \int_{t_1}^{t_2} f_a(t)\, dt$$

At the simplest level, these principles can be modeled by a dynamic system of homogeneous producers and homogeneous consumers with constant production and consumption rates, c and d respectively. The equations below define the equilibrium state for this simple example:

$$\sum_{h \in H} \int_{t_1}^{t_2} F_h(t)\, dt = \sum_{a \in A} \int_{t_1}^{t_2} f_a(t)\, dt$$

$$\sum_{h \in H} \int_{t_1}^{t_2} c\, dt = \sum_{a \in A} \int_{t_1}^{t_2} d\, dt$$

$$|H| \times c \times (t_2 - t_1) = |A| \times d \times (t_2 - t_1)$$

$$|A| = |H| \frac{c}{d}$$

This is essentially a species-based analysis of our individual-based ecological control system.

4 Initial Results and Conclusions

4.1 Initial Results

We have performed a set of initial experiments utilysing a real agent system over a wired network to prove the validity of our approach. The experiments have been executed with homogeneous producers and homogeneous consumers. The production rate is $c = 1$ and the consumption rate is $d = 5$. The resulting equilibrium state requires $|A| = |H|/5$.

Agents wander randomly with uniform distribution across all active hosts on the network, performing tasks and collecting food associated with the tasks. Agents are terminated if the food in their internal food bank drops below 0. An agent that acquires 100 units food will reproduce, spawning a new agent and splitting its food resources in half. As the system can enter a state with no agents, we have employed a recovery strategy where each host can spawn a new agent if the food level exceeds a fuzzy threshold of 60 ± 30 units.

We have run 3 sets of experiments on 4, 8 and 10 hosts, performing 30 trials of each. A single trile consists of starting a system with a singel agent and alowing agents to to stabilyse their number for the duration of the trial (10 to 15 minutes). The number of agents in the system is recorded five times a second, and the average over all trials is plotted in the corresponding section of Figure 1. The actual number of agents is plotted by line 1 along with the avarege number of agents across the duration of experiment (line 2) and the theoretically predicted number of agents (line 3) for comparison. Although exhibiting some oscillation, the system converges to the predicted theoretical value, and exhibits performance over time that is remarkably close (within 6%, 10% and 1% for experiments with 4, 8 and 10 hosts respectively) to the theoretical value. Since the optimal number of agents is fractional in experiments with 4 and 8 hosts the exact target could never be achieved. Instead system is oscillates around it thous achieing the target on average.

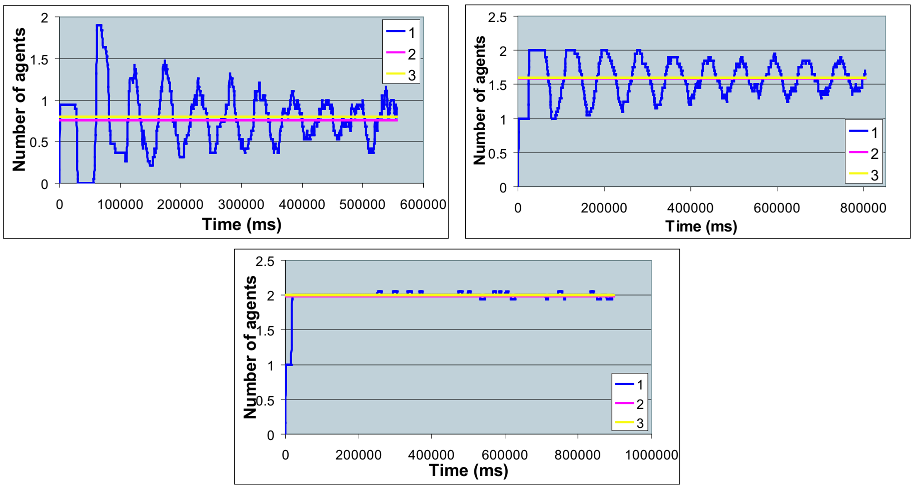

Fig. 1. Illustration of individual test runs for 4, 8 and 10 hosts

4.2 Conclusions and Future Work

This paper developed an ecology-based model for managing a number of agents on the adhoc wireless networks. We have discovered that ecosystem based model can provide decentralised distributed robust control of agents in the dynamic and uncertain network enviroments. Our approach involves a novel exploitation of properties of ad hoc networks, enabling mobile agents to automatically adapt to changes that affect their communication and migration. The capability to dynamically reason about the state of their network will provides new possibilities for stable MAS.

In the future we are planning more extensive set of experiments utilizing a simulation as well as live Secure Wireless Agent Testbed (SWAT) [20]. We also would like to create more detailed mathematical model of such systems to be able to predict and control the emergent behavior of agent system.

References

1. J. M. Alexander. Evolutionary game theory. In E. N. Zalta, editor, *The Stanford Encyclopedia of Philosophy.* Stanford University, Summer 2003.
2. Donovan Artz, Max Peysakhov, and William C. Regli. Network meta-reasoning for information assurance in mobile agent systems. In *IJCAI*, pp 1455–57, 2003.
3. A. Assad and N. Packard. Emergent colonization in an artificial ecology. In F. Varela and P. Bourgine, editors, *Toward A Practice of Autonomous Systems: Proc. of the First European Conf. on Artificial Life.*, pp 143–152. MIT Press, 1992.
4. M. Conrad and H.H. Pattee. Evolution experiments with an artificial ecosystem. *J. Theoret. Biol.*, 28:393–409, 1970.
5. M. Conrad and M. Strizich. Evolve ii: A computer model of an evolving ecosystem. *BioSystems*, 17:245–258, 1985.
6. Gary William Flake. *The Computational Beauty of Nature: Computer Explorations of Fractals, Chaos, Complex Systems, and Adaptation.* MIT Press, July 1998.
7. Felix C. Gartner. Fundamentals of fault-tolerant distributed computing in asynchronous environments. *ACM Computing Surveys*, 31(1):1–26, 1999.
8. D. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning.* Addison-Wesley Pub Co, December 1989.
9. S. Goldenstein, E. Large, and D. Metaxas. Non-linear dynamical system approach to behavior modeling. *The Visual Computer*, 15:349–364, 1999.
10. J. R. Koza, F. H. Bennett III, F. H. Bennett, D. Andre, and M. A. Keane. *Genetic Programming III: Automatic Programming and Automatic Circuit Synthesis.* Morgan Kaufmann Publishers, 1999.
11. S. Kraus, V.S. Subrahmanian, and N. Cihan Tacs. Probabilistically survivable mass. In IJCAI, pp 789–795, 2003.
12. Sanjeev Kumar, Philip R. Cohen, and Hector J. Levesque. The adaptive agent architecture: Achieving fault-tolerance usingpersistent broker teams. Technical Report CSE-99-016-CHCC, 23, 1999.
13. K. Lerman and A. Galstyan. A general methodology for mathematical analysis of multi-agent systems. Technical Report ISI-TR-529, USC Info. Sciences, 2002.
14. K. Lerman and A. Galstyan. Macroscopic analysis of adaptive task allocation in robots. Submitted to IROS-03, 2003.
15. O. Marin, P. Sens, J. Briot, and Z. Guessoum. Towards adaptive fault tolerance for distributed multi-agent systems. In *AAMAS: part 2*, pp 737 – 744, 2002.
16. J. Maynard-Smith. *Evolution and the Theory of Games.* Cambridge University Press, Cambridge, 1982.
17. J. Maynard-Smith, G. Price. The logic of animal conflict. *Nature*, 146:15–18, 1973.
18. R. L. Olson and A. A. Sequeira. An emergent computational approach to the study of ecosystem dynamics. *Ecological Modeling*, 79:95–120, 1995.
19. M. Rizki and M. Conrad. Evolve iii: A discrete events model of an evolutionary ecosystem. *BioSystems*, 18:121–133, 1985.
20. Evan Sultanik, Donovan Artz, Gustave Anderson, Moshe Kam, William Regli, Max Peysakhov, Jonathan Sevy, Nadya Belov, Nicholas Morizio, and Andrew Mroczkowski. Secure mobile agents on ad hoc wireless networks. In *The Fifteenth Innovative Applications of Artificial Intelligence Conference*, pp 129–36. American Association for Artificial Intelligence, Aug 2003.
21. Taylor, E. Charles, Turner, Scott, and Seth R. Goldman. Ram: Artificial life for the exploration of complex biological systems. In C.G. Langton, editor, *Artificial Life: SFI Studies in the Sciences of Complexity.*, pp 275–295. Addison-Wesley, Redwood City, CA, 1989.