Agent-Based Resource Allocation in Dynamically Formed CubeSat Constellations

(Extended Abstract)

Chris HolmesParker
Oregon State University
204 Rogers Hall
Corvallis, OR 97331
holmespc@onid.orst.edu

Adrian Agogino
UCSC, NASA Ames
Mail Stop 269-3
Moffett Field, CA 94035
Adrian.K.Agogino@nasa.gov

ABSTRACT

In the near future, there is potential for a tremendous expansion in the number of Earth-orbiting CubeSats, due to reduced cost associated with platform standardization, availability of standardized parts for CubeSats, and reduced launching costs due to improved packaging methods and lower cost launchers. However, software algorithms capable of efficiently coordinating CubeSats have not kept up with their hardware gains, making it likely that these CubSats will be severely underutilized. Fortunately, these coordination issues can be addressed with multiagent algorithms. In this paper, we show how a multiagent system can be used to address the particular problem of how a third party should bid for use of existing Earth-observing CubeSats so that it can achieve optical coverage over a key geographic region of interest. In this model, an agent is assigned to every CubeSat from which observations may be purchased, and agents must decide how much to offer for these services. We address this problem by having agents use reinforcement learning algorithms with agent-specific shaped rewards. The results show an eight fold improvement over a simple strawman allocation algorithm and a two fold improvement over a multiagent system using standard reward functions.

Categories and Subject Descriptors

I.2.11 [**Computing Methodologies**]: Artificial Intelligence—*Multiagent systems*

General Terms

Algorithms, Management, Performance

Keywords

CubeSat, Multiagent Systems, Negotiation

1. INTRODUCTION

Collaborative networks of CubeSats offer mission capabilities that are impractical for larger satellite platforms, including simultaneous in situ measurements of multiple locations in space and temporally separated measurements of precise points in space [3]. They also offer lower cost and increased robustness compared to traditional satellites due to the low cost of COTS components and system reconfigurability. In addition, networking clusters of CubeSats together in order to boost performance is becoming a popular concept, similar to networking multiple computers together into clusters to increase computational capabilities [1].

While considerable effort has been put into reducing the cost of CubeSats and increasing their capability, little work has been done on how to coordinate all these resources once they are in orbit. A good way to address this issue is through the use of multiagent learning methods.The development of multiagent coordination algorithms that allow CubeSats to share resources, allocate tasks, and dynamically form partnerships will allow tremendous flexibility in the way CubeSats are deployed. These capabilities could revolutionize the way space research is performed by enabling a large community of universities and institutions to readily share satellite resources, opening up new avenues of research, and greatly reducing the cost barrier associated with space research that has limited advancements for decades.

The algorithm presented in this work is designed to handle two problems at once, in a robust way: 1) how to obtain a distributed set of resources (CubeSats), such that the total collection of resources performs a task in a cost-effective way, and 2) how to bid for these resources with unreliable sellers. We address this problem by using a multiagent learning system, in which each individual agent must learn to bid for a resource, such that the collective set of bids of all agents is likely to obtain an amount of resources that will optimize the system level performance objective.

2. SATELLITE COORDINATION PROBLEM

In this work, we look at a model where we assume CubeSats are owned by separate institutions, and that the values of each Cubesat's observations to its institution are constantly changing based upon its position in orbit. We also assume that a third party knows the approximate value of these satellites to their own institution, within a probability distribution. The overall problem then becomes: how this third party can make bids for the observational capabilities of these satellites to obtain an optimal return. If bids are too small, then too few observations are made and the return is small. If bids are too large, then too many observations are made and the observational benefit is not worth

Cite as: Agent-Based Resource Allocation in Dynamically Formed CubeSat Constellations (Extended Abstract), HolmesParker, C. and Agogino, A., *Proc. of 10th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS 2011)*, Tumer, Yolum, Sonenberg and Stone (eds.), May, 2–6, 2011, Taipei, Taiwan, pp. 1157-1158.

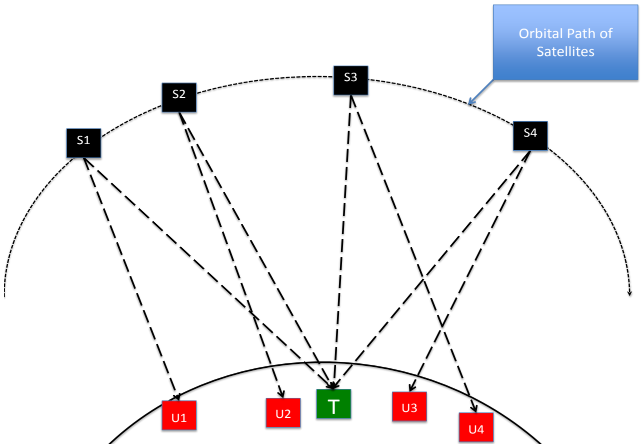

Figure 1: A third party wishes to have a set of university owned CubeSats take observations of a point of interest (POI), T. While university s_i will usually want to observe its own POI u_i, it will be willing to make an observation of T if it is paid more to do so than the value of it's observation of u_i.

the cost. Even worse, if observations have diminishing returns, then large bids will result in too many observations of even smaller value. Our approach to this problem entails assigning a single agent to each satellite which decides how much to bid for the use of the satellite's observational capability at any given time. We then have the problem of how to coordinate all of the agents' bids to receive an optimal collective return. We address this problem with reinforcement learning techniques that maximize agent-specific rewards which are shaped to speed up learning while promoting high-performance solutions.

2.1 System Objective

The overall objective is to try to obtain the greatest total value of observations at the least cost. While computing the total cost is rather straightforward, the total value of the observations heavily depends upon the domain. In this paper, the total value of all observations is a sub-linear function of the sum of the squares of the values of all observations.

$$G_N(V,C) = \sqrt{a\sum_i {V_i}^2} - a\sum_i C_i \ , \qquad (1)$$

where a is a constant, V_i is the value of the information gained from the use of CubeSat i, and C_i is the cost of acquiring resources from CubeSat i. This nonlinear objective function provides diminishing returns for increasing levels of information. As in many real world problem domains, there exists a saturation point, beyond which additional information or resources become less beneficial for the system, even if the per unit cost remains constant.

3. EXPERIMENTS

We tested five different types of agents, and compared their effectiveness in optimizing system objective.

3.1 Agent Types

In these experiments, the five types of agents used are as follows:

1. **Random**: Agents take random actions (R).
2. **Strawman**: An agent's bid is precisely equal to the value of a satellite to its university (S).
3. **Local**: Agents try to maximize a local objective (L).
4. **Global**: Agents try to maximize system objective (G).
5. **Difference**: Agents try to maximize difference objective (D), shown previously to lead to fast learning [5].

3.2 Experimental Results

This set of experiments tests the performance of the five types of agents (R, L, S, G, D) in a noisy environment with 100 satellites. Figure 2 shows the performance of each reward function. In all cases, performance is measured by the same global reward function, regardless of the reward function used to reward the agents in the system. As seen, both agents using G and D performed adequately in this instance, although agents using D perform better. Agents using D are able to perform better because an individual agent has more influence over its own difference reward than on the system reward, allowing it to learn faster. L performs the worst, showing that greedy self-interested agents do not always perform well in coordination tasks. S and R also perform poorly.

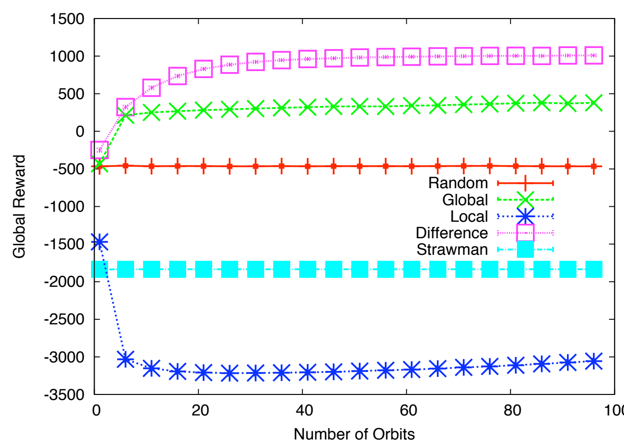

Figure 2: Performance of a 100-satellite system for R, L, S, D, and G agents within a noisy environment.

4. REFERENCES

[1] O. Abdelkhalik and D. Mortari. Satellite constellation design for earth observation. *15TH AAS/AIAA Space Flight Mechanics Meeting*, 2005.

[2] B. Klofas, J. Anderson, and K. Leveque. A survey of cubesat communication systems. Technical report, California Polytechnic State University, 2008.

[3] R. Sandau, H. Roser, and A. Valenzuala, editors. *Small Satellite Missions for Earth Observations: New Developments and Trends*, New York, NY, 2010. Springer Heidelburg Dordrecht London.

[4] R.S. Sutton and A.G. Barto. *Reinforcement learning: An Introduction*. MIT Press, Cambridge, MA, 1998.

[5] K. Tumer and D. Wolpert, editors. *Collectives and the Design of Complex Systems*. Springer, New York, 2004.