Trade-Offs in Cooperative Goal Seek using Nano-Devices

S. Chandrasekaran and D. F. Hougen

Robotics, Evolution, Adaptation, and Learning Laboratory (REAL Lab)
School of Computer Science, 200 Felgar Street, Room 144
University of Oklahoma, Norman, OK 73019, USA
sree@ou.edu, hougen@ou.edu

ABSTRACT

Micro and nano-scale devices and systems require not only nano-scale components but also minimal hardware design and control methodologies. When constructing mobile nano-devices, the numbers of motors and sensors should be reduced and the control algorithms should be simplified, whenever possible. However, such reductions may result in sub-optimal performance. We consider here the potential trade-offs between two configurations of nano-devices performing a cooperative goal-seeking task. In the complex configuration, each nano-device has multidirectional sensing and controlled multidirectional locomotion. In the simple configuration, each nano-device can sense only at its present location and can move in a straight line or at random. Using simulation at a high level of abstraction we show that performance using the simpler configuration depends greatly on resampling rate.

Keywords: nano-devices, control

1 INTRODUCTION

Ongoing development in nanotechnology, bionanotechnology [1] and synthetic biology [2] may eventually lead to the construction of nano devices called *nano-robots* [3]. A nano-robot is a nano-scaled device in which sensing and action are coupled by intelligent decision-making, as they are in macro-scaled robots [4]. Due to their size, these nano-devices are ideal tools for applications such as nano-medicine, environmental remediation, and production of alternative energy sources.

Cao et al. [5] provide an excellent overview of cooperative mobile robotics research, much of it inspired by biology, as is our own. Lewis and Bekey consider swarm intelligence and chemical signaling techniques for nano-scaled robots applied to the problem of tumor removal [6]. They introduce the concept of chemical *guide-posts*, which their simulated nano-robots use to speed navigation to a target at the cost of increased complexity in the nano-robots themselves.

Many other interesting works use similar concepts for cooperative micro- and macro-scale devices. Some researchers have adopted similar means for robot communication using virtual pheromones (e.g., [7]). Parker et al. [8] investigate cooperative behavior of robot systems and find that the performance of the system changes greatly by varying the quorum threshold value.

Here we extend our previous work [9] by, in effect, sub-sampling the environment used previously by re-scaling all components by a factor of four in each dimension. These results will help in the design of nano-devices by more closely investigating the design strategies previously introduced.

2 NANO INTELLIGENCE

Robots are developed to assist in many activities. To do that, robots need to act intelligently and with appropriate autonomy. Macro-scaled robots can possess enormous processing power and sensory capabilities whereas accomplishing a complex task using nano robots requires strategies that accommodate their size limitations.

Though nano-robots face limitations such as (1) low memory capacity, (2) limited sensory and motor capabilities, and (3) low-level intelligence, they are indeed capable of accomplishing difficult tasks by acting in concert rather than working as individual agents. Techniques like *swarm intelligence* and *quorum sensing* can make nano-robots practical tools to assist in nano-scaled tasks such as targeting and/or removing tumor cells or delivering drugs at precise locations.

2.1 Swarm Intelligence

Ants, fish, birds, and many other animals exhibit emergent behaviors in groups. Difficult tasks such as finding food or migrating are more successfully accomplished by these animals when they act together. This swarm intelligence [10] helps these agents accomplish complex behaviors. Similarly, individually insignificant nano-robots are also capable of performing difficult tasks by acting in concert rather than working alone.

2.2 Quorum Sensing

Communication can improve group coordination. In nature, ants leave pheromone trails as they forage for food. These trails are sensed and reinforced by other ants as they forage. This type of coordination may be achieved through chemical signals, visual cues, etc., communicated between agents. At micro- or nano-levels, communication through chemical signals is preferred.

Quorum sensing is the ability of bacteria coordinate behavior via signaling molecules [11]. Quorum sensing is a highly evolved and effective tool for many activities. For example, communication in a bacterial colony infecting a host is accomplished using chemical signals.

Inspired by the quorum sensing chemical dispersion and sensing abilities of bacteria, we use these capabilities for collaborative goal seeking. The new group coordination behavior of our nano-robots emerges based on a communication process using chemical signaling.

3 RESEARCH OBJECTIVES

Regardless of a robot's size, *goal-seeking* is important for successful performance in many tasks. In this research, we develop and compare different collaborative goal-seeking strategies appropriate for nano-robots.

The goal-seeking behavior is realized as follows. On injection into the environment, robots move while looking for a target using specialized sensors. On reaching the target, a nano-robot releases an *inducer*, that is, a quorum signaling chemical which can be received by other nano-robots to help them home to the target. When the signal strength reaches a threshold value, the nano-robots know that there are enough robots present at the target site that they can now perform their designated task (say, destroying a tumor).

The objective of this research, which is an extension of our previous work [9], is to study the trade-offs involved in goal-seeking with robots of different complexity levels and to determine in what ways the complexity of the robots impacts the effectiveness of their search in a scaled-up simulation environment.

3.1 Strategies Studied

With this objective in mind, we have considered the following three different goal-seeking strategies.

3.1.1 Multi-Directional Sensing and Motion—(Strategy 1)

This is the most complex strategy that we have considered. Each robot can sense and compare the signal strength present to its immediate front, left, and right and move to the higher concentration. To use this type of sensing and motion model in two dimensions, each robot requires three sensors and at least two motors.

3.1.2 Mimic Bacterial Sensing and Motion—(Strategy 2)

This medium complexity strategy mimics a common bacterial sensing and motion pattern [12]. At pre-defined time intervals, each robot samples the environment for chemical gradient values. Based on the values, robots choose between two types of movement—*tumble* or *run*. The nano-robot will tumble (move randomly) more in the absence of a gradient or if there is a decreasing gradient. On the other hand, nano-robots run (move straight) more often in the presence of an increasing gradient.

Tumbling and running result from different flagellar rotational movement. The bacterium runs when the flagellum rotates counter-clockwise, whereas it tumbles when the flagellum is rotated clockwise. This strategy allows the nano-robot to have a very simple construction; it is sufficient to have one sensor and one motor.

3.1.3 Random Motion (Strategy 3)

The simplest motion strategy is random. This is the baseline to which we compare the other goal-seeking strategies. Here, no gradient sensing takes place for navigation; each robot finds the target only upon contact. The inducer is sensed only to determine a quorum has been achieved and one motor is present for locomotion.

4 EXPERIMENTS

Each nano-device, irrespective of goal-seeking strategy, can sense the target on contact. On sensing the target, it releases an inducer in order to communicate with other nano-robots about the presence of the target.

4.1 Environment Setup

All experiments are done using NetLogo, which "is a programmable modeling environment for simulating natural and social phenomena" [13]. NetLogo provides a highly abstract environment to visualize and test our goal-seeking strategies. Fig. 1 shows the NetLogo screen of the simulation using the small-scaled environment.

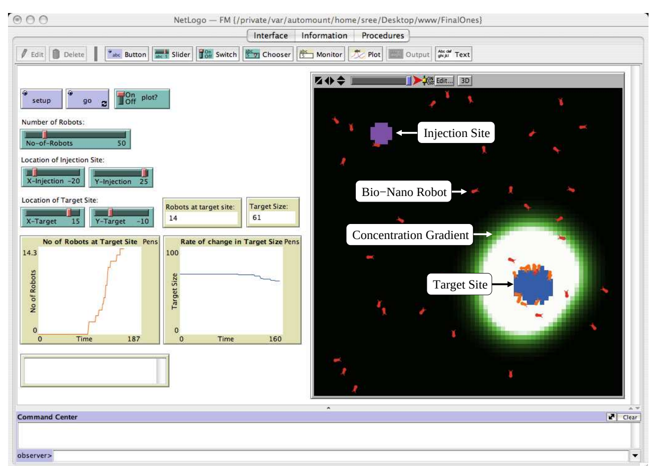

Figure 1: NetLogo during simulation execution with annotated objects of interest. Shown at smaller scale.

4.1.1 Initial Robot Swarm Setup

All the experiments are carried out with following initial robot swarm setup:

- Swarm Size: 50 nano-robots.
- All robots in a swarm exhibit the same goal-seeking behavior.
- All robots are released from the *injection site*—a specific entry place in the environment.
- The mission is successful upon some percentage of the robots reaching the specific location in the environment called the *target site*.

4.1.2 Robot Setup

The following are the setup conditions for each nano-robot:

- There is no limit on the lifetime for each robot.
- Each robot has 60 units of inducer and has sensors capable of sensing the inducer.
- Each robot has target sensors on it's surface.
- Each robot stops moving on target contact and starts releasing 1.5 units of inducer each time step.

4.1.3 Environment Setup

We have increased the size of the environment by a factor of four in both the x and y dimensions over that used in our previous setup. The following are the environment setup conditions in the NetLogo simulator:

- Bounded Area: 284 x 284 Cells
- Target Size: 1245 Cells
- Distance from injection site to target: 148 Cells
- Inducer is diffused around the target and evaporates over time.
- Diffusion Rate: 90%
- Evaporation Rate: $\sim$1%

4.2 Experiment Cases

Seven different cases are considered. Each case is repeated 30 times.

Case 1: Strategy 1, each robot samples the environment for the inducer at every time step.

Case 2: Strategy 1 where each robot samples the environment for the inducer every 4 time steps.

Case 3: Strategy 2 where each robot samples the environment for the inducer at every time step.

Case 4: Strategy 2 where each robot samples the environment for the inducer every 2 time steps.

Case 5: Strategy 2 where each robot samples the environment for the inducer every 3 time steps.

Case 6: Strategy 2 where each robot samples the environment for the inducer every 4 time steps.

Case 7: Strategy 3.

4.3 Experimental Results

Results in this setup, which is four times larger in each dimension than previously, are similar to our previous results but important new results are found. All of these results are statistically significant at a confidence level of 95% or greater. Fig. 2 depicts the results.

As before, Strategy 1 (Multi-Directional Sensing and Motion) is the most efficient. Here we also consider the effect of sampling rate on this strategy, which was not considered in our previous work. At both sampling rates considered, Strategy 1 is more efficient than all other strategies. However, the increased sampling rate considered does not improve performance for Strategy 1. It remains as future work to consider whether a slower sampling rate would negatively effect Strategy 1.

In Strategy 2 (Bacterial Sensing and Motion), robots are much simpler in construction. The robots were tested using four different sampling rates. Of these, the best versions used a sampling rate of 1 or 2 time steps and the worst versions used a sampling rate of 3 or 4 time steps. The best versions were still slower to the target than the Multi-Directional Sensing and Motion strategy. The worst versions were similar to the Random Motion strategy. The performance of the bacterial model was related to the sampling rate; the higher the sampling rate, the faster the robots were able to reach the target site. However, the relationship was not straightforward as the performance curves were grouped together—there was no significant difference between sampling rates of 1 and 2 time steps, nor between sampling rates of 3 and 4 time steps. The cause of this clustering remains to be determined.

The Random Motion model (Strategy 3), performed worst in the re-scaled environment, which suggests that good performance of the nano-robots does rely on some means of communication between them.

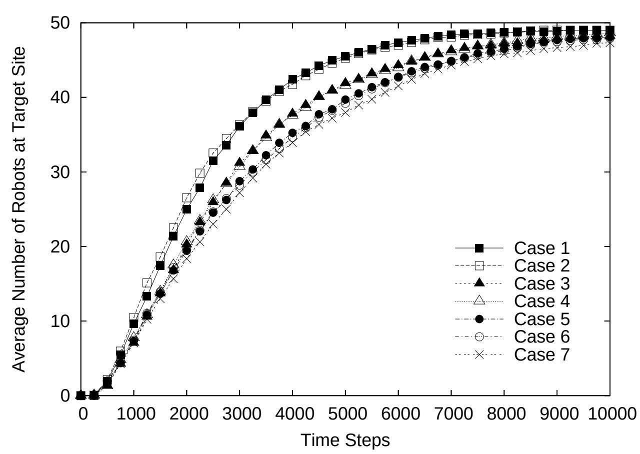

Figure 2: Performance graph showing the performance of all seven cases, averaged over 30 repetitions of each case, each case plotted every 250 time steps.

5 DISCUSSION & FUTURE WORK

In our new experiments, higher complexity still results in more efficient performance. The performance of these models gives an apparent trade-off between complex structures and efficient results. However, we are yet to explore the limits of these trade-offs. We have reached the approximate limits of the NetLogo simulator as presently coded while we have yet to determine if the Bacterial Sensing and Motion model will continue to improve in performance as the sampling rate is increased. Note that, while the system did not improve as the sampling rate was increased from two time steps to one at the current resolution, it also did not improve as the sampling rate was increased from four time steps to three yet *did* improve as the sampling rate was increased from three time steps to two. The non-uniform nature of the improvements suggests that firm conclusions should not be drawn from the lack of improvement between the highest two sampling rates.

Our future work, then, will include continuing to increase the resolution of our simulations in order to find the limits of the Bacterial Sensing and Motion model (continuing to use NetLogo if we are granted access to the source code or if it is recoded for us; abandoning NetLogo otherwise). It will also include testing the sensitivity of the more complex Multi-Directional Sensing and Motion model to *slower* sampling rates.

Our future work will also include simulating the various models in a three-dimensional setup. This extension is a necessary one as the natural world contains three spatial dimensions. In three dimensions, the nanorobots executing the Multi-Directional Sensing and Motion strategy would need to increase in physical complexity, i.e., they would each need at least three motors to move in any direction, whereas the complexity of the bio-nano robot carrying out the Bacterial Sensing and Motion model would remain unchanged.

We are also planning to develop another baseline motion model. In this model, the motion of the nano-robots will be mostly in straight lines with noise added to the system at different levels; the noise is mainly due to the random Brownian motion that affects the straight-line motion of nano-scale organisms in real world. Naturally, we would compare all models under similar noise levels, to determine how robust they are to such noise.

6 ACKNOWLEDGMENTS

We thank the other members of the Robotics, Evolution, Adaptation and Learning Laboratory (REAL Lab), School of Computer Science, University of Oklahoma for their valuable suggestions and advice at the every stage of this research work. We extend our thanks to Dr. Andrew Fagg, Dr. Thomas Ray, and Dr. William Hildebrand for their insightful views and discussions.

REFERENCES

[1] D. S. Goodsell, *Bionanotechnology: Lessons from Nature*. Wiley-Liss, 2004.

[2] D. Endy, "Foundations for engineering biology," *Nature*, vol. 438, pp. 449–453, Nov. 2005.

[3] A. A. G. Requicha, "Nanorobots, NEMS, and nanoassembly," in *Proceedings of the IEEE*, vol. 91, no. 11, Nov. 2003, pp. 1922–1933.

[4] R. R. Murphy, *Introduction to AI Robotics*. Cambridge, MA: MIT Press, 2000.

[5] Y. U. Cao, A. S. Fukunaga, and A. B. Kahng, "Cooperative mobile robotics: Antecedents and directions," *Autonomous Robots*, vol. 4, no. 1, pp. 7–27, Mar. 1997.

[6] M. A. Lewis and G. A. Bekey, "The behavioral self-organization of nanorobots using local rules," in *Proceedings of the lEEE/RSJ International Conference on Intelligent Robots and Systems*, vol. 2, 1992, pp. 1333–1338.

[7] D. Payton, M. Daily, R. Estowski, M. Howard, and C. Lee, "Pheromone robotics," *Autonomous Robots*, vol. 11, no. 3, pp. 319–324, Nov. 2001.

[8] C. A. C. Parker and H. Zhang, "Biologically inspired decision making for collective robotic systems," in *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, vol. 1, 2004, pp. 375–380.

[9] S. Chandrasekaran and D. F. Hougen, "Swarm intelligence for cooperation of bio-nano robots using quorum sensing," in *Proceedings of 2nd ASM–IEEE EMBS Conference on Bio-, Micro- and Nanosystems*, 2006, to appear.

[10] E. Bonabeau, M. Dorigo, and G. Theraulaz, "Swarm intelligence: From natural to artificial systems," *Journal of Artificial Societies and Social Simulation*, vol. 4, no. 1, 2001.

[11] M. B. Miller and B. L. Bassler, "Quorum sensing in bacteria," *Annual Review of Microbiology*, vol. 55, pp. 165–199, Oct. 2001.

[12] H. C. Berg, "Motile behavior of bacteria," *Physics Today*, vol. 53, no. 1, pp. 24–29, 2000.

[13] U. Wilensky, "NetLogo," Evanston, IL, 1999, accessed 15 February 2006. [Online]. Available: http://ccl.northwestern.edu/netlogo