Toward Human Interaction with Bio-Inspired Teams*

(Extended Abstract)

Michael A. Goodrich
Brian Pendleton
Brigham Young University
Provo, UT, USA
mike@cs.byu.edu
brianpen@byu.net

P.B. Sujit
Jose Pinto
University of Porto
Porto, Portugal
sujit@fe.up.pt
zepinto@fe.up.pt

Jacob W. Crandall
Masdar Institute of Technology
Abu Dhabi, UAE
jcrandall@masdar.ac.ae

ABSTRACT

Although much work has been done on designing autonomy and user interfaces for managing small teams of independent robots, much less is known about managing large-scale bio-inspired robot (BIRT) teams. In this paper, we explore human interaction with BIRT teams in an information foraging task. We summarize results from two small experiments that use two types of BIRT teams in a foraging task. The results illustrate differences in BIRT performance for different types of human interaction, and illustrate how performance robustness can vary as a function of interaction type.

Categories and Subject Descriptors

I.2.9 [**Computing Methodologies**]: Robotics—*Operator interfaces*

General Terms

Human Factors

Keywords

human-robot cooperation, biologically-inspired robot teams

1. INTRODUCTION

Two current research areas are receiving considerable attention in the recent literature: human-robot interaction (HRI) and bio-inspired robot teams (BIRT). HRI emphasizes the design of robot behaviors that respect and support human psychological principles. BIRT research emphasizes identifying principles and practices of biological societies such as ants and bees and then abstracting and encoding these principles in robots [5]. HRI helps humans design robots that are *responsive* to human input and BIRT helps humans design teams that are *robust*. Research that combines elements of HRI with BIRT should allow humans to design robot teams that are both responsive and robust. We call the combination human-BIRT (HuBIRT) to emphasize human-centered design of bio-inspired teams.

We apply HuBIRT to a foraging task where there are multiple tasks that appear at unknown locations in a spatial domain. Agents must discover the tasks, assign a subset or subteam of the agents to perform the task, and persist until the task is complete. New tasks randomly appear. Bio-inspired agents are capable of performing some aspects of this task by themselves, but are generally inefficient at the task without having some kind of human input.

We analyze how human input can influence two kinds of bio-inspired teams: one based on a physicomimetic model and the other based on a biomimetic model. In contrast to this approach, agent-based simulation has been used in HuBIRT to determine team organizational aspects/parameters of a team by finding a relationship between parameters and team behavior [7, 3], while leader-based models were explored in [2, 4].

2. PHYSICOMIMETICS

In a physicomimetics model, all agents experience inter-agent attraction that draws agents together and inter-agent repulsion that keeps agents from getting too close. These forces can produce collective behavior based on very simple agent autonomy. Each agent is treated as a particle that calculates the force acting on it by other agents using equations in [6]. Since these agents are not goal-driven, responsive collective behavior can benefit from human influence.

Attraction Repulsive Control (ARC). In ARC, the operator uses a virtual agent to attract (influence) the real agents in the field. Once, the agents are attracted, the operator drags the virtual agent to the resource location. This makes the agents responsive to a given individual task but, the operator is required to be in the loop throughout the mission. As the number of tasks grows, operator and communication channel can quickly become overloaded.

Leader Model (LM). In LM, the operator manages a small number of leader agents. Once a leader agent is assigned to a task, it recruits other agents and pulls them to the resource location. The attraction radius of influence is assigned by the operator and also the location of the resource.

Results. We simulated a swarm of 100 agents with 10 leader agents (for LM). Figure 1 illustrates performance for the ARC and LM as the probability of communication P is varied between $1, 0.5, 0, 1$ and 0.01. LM always performed better than ARC. This is because the operator can assign a leader to a target, choose a desired radius of influence, and then switch attention to another assignment. By contrast, in the ARC case, the operator is attached to a set of agents until the target is minimized. Thus, the response time for

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LM model is lower than for ARC model.

ARC performs poorly for $P < 1$ (see Figure 1) because it requires nearly constant communication between the virtual and other agents. By contrast, LM performance degrades only slightly with decrease in P, indicating robust performance. The leader at every time step, tries to attract more agents as it moves towards the resource location. Once, the agent is attracted to the leader, the agent is programmed to follow the leader and hence the swarm does not fluctuate.

3. BIOMIMETICS

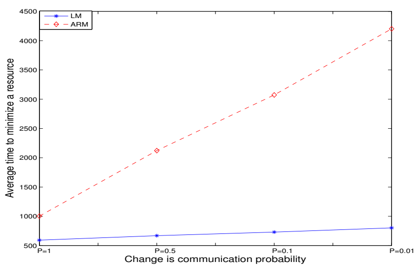


Figure 1: Avg. response time vs. P.

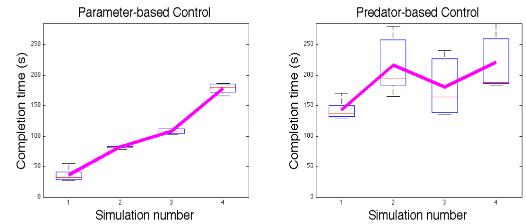
Consider the biomimetics model from [1]. In this model, agents emulate fish by using prioritized behavioral rules to tell a fish to change its desired direction as a function of the distance and direction of neighbors within a specified "zone of repulsion,", "zone of orientation," "zone of attraction", and "blind zone". The scenario consists of 100 fish in a 120×120 area. Quantities of food (represented graphically as barrels) are placed around the map to represent the information to be gathered. The "food" is depleted at 1 unit per second per fish whenever a fish is within range.

Parameter-Based Management (PAR). In PAR, fish behavior is determined by an operator offline by selecting parameters that cause fish to spread out and keep a minimum distance from each other. The fish spread out over the map and consume food they come in contact with. In simulation, the parameter values were subjectively optimized to perform best for small sources of food located in a uniform grid.

Predator-Based Management (PRED). In PRED, and operator controls a single predator to split and steer groups of aligned fish; fish are repelled by a predator if the predator is within a prescribed distance. The predator moves slightly faster than the fish and can turn much more sharply. Collectively, the fish are clustered in a small group, but if a predator gets close then they are repelled by this predator. Parameters are chosen such that fish tend to stay close together even when the predator "chases" them.

Results. Four simulations were conducted. In the first two simulations, food was placed in a uniform grid, 10 units apart; each container held one resource unit. The second simulation again placed food in a uniform grid, but the size of the containers was increased to 10 resource units. In the third simulation, 10 containers of food are randomly placed using a uniform distribution on x and y. This scenario is designed to require fish to coordinate in schools, when the size of the food containers is large. To make the total amount of resource comparable to the second simulation, each food container held 100 resource units. In the fourth simulation, 200 resource units were placed in each barrel.

Average results over five trials are shown in Figures 2(a)-2(b). The plots include the mean, the interquartile range, and the range. The thick magenta line shows the trends of the average values.



(a) (b)

Figure 2: Completion time for (a) parameter-based management and (b) predator-based management.

PAR completed the tasks more quickly for all simulations. Uniformly spreading the fish out in all directions produces collectively fish that cover the area effectively. The predator-managed fish travel in schools and, therefore, take more time to cover the whole map. Note the trends between the second through fourth simulations. PRED stays fairly constant but PAR increased. This is because PRED allowed a school of fish to focus on a concentrated resource for a long period of time, whereas PAR equired the fish to continue to move about randomly, being repelled by each other on occasion or when the came near to walls. The predator approach seems to be potentially more robust to variations in the concentrations and distributions of the resources.

4. SUMMARY

This paper illustrates how leader-based and predator-based interactions can help a human robustly manage a bio-inspired robot team.

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