2013-12-01

Shaping Swarms Through Coordinated Mediation

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A thesis submitted to the faculty of
Brigham Young University
in partial fulfillment of the requirements for the degree of

Master of Science

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December 2013

ABSTRACT

Shaping Swarms Through Coordinated Mediation

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A swarm is a group of uninformed individuals that exhibit collective behaviors. Without any information about the external world, a swarm has limited ability to achieve complex goals. Prior work on human-swarm interaction methods allow a human to influence these uninformed individuals through either leadership or predation as informed agents that directly interact with humans. These methods of influence have two main limitations: *(1)* although leaders sustain influence over nominal agents for a long period of time, they tend to cause all collective structures to turn in to flocks (negating the benefit of other swarm formations) and *(2)* predators tend to cause collective structures to fragment. In this thesis, we present the use of *mediators* as a novel form for human-swarm influence and use mediators to shape the perimeter of a swarm. The mediator method uses special agents that operate from within the spatial center of a swarm. This approach allows a human operator to coordinate multiple mediators to modulate a rotating torus into various shapes while sustaining influence over the swarm, avoiding fragmentation, and maintaining the swarm's connectivity. The use of mediators allows a human to mold and adapt the torus' behavior and structure to a wide range of spatio-temporal tasks such as military protection and decontamination tasks. Results from an experiment that compares previous forms of human influence with mediator-based control indicate that mediator-based control is more amenable to human influence for certain types of problems.

Keywords: Shaping Swarm, Swarm Intelligence, Multi-agents System, Human Swarm Interaction, Swarm Robotics.

ACKNOWLEDGMENTS

I would like to express the deepest appreciation to my advisor, Dr. Goodrich, who has the substance of a genius and the spirit of understanding and patience. His inspirational thoughts and comments helped me to finish my degree fulfillment. I am also grateful to Dr. Seppi and Dr. Barrett who are my second and third committee members for their great examples and devotions while I was taking their classes. I am grateful for their supports to finish my thesis as well.

I am grateful to my parents, who live on the other side of the earth, for their love and support. Thanks to all Human Centered Machine Intelligence Lab-mates for being great friends and mentors.

Table of Contents

List of Figures

List of Tables

Chapter 1

Background, Motivation, and Overview

In many problem domains that involve risks such as military protection, search and rescue, and decontamination task, it is desirable to have robots perform the tasks instead of humans. For the better performance and flexibility of robots in the tasks, multiple robots are potentially required. This type of environment that is composed of interacting multiple intelligent agents is defined as multi-agent system.

In multi-agent system, Crandall and Goodrich stated that performance of a semi-autonomous robot decreases when the robot is neglected by a human operator, when the complexity of the world increases, or both [8]. The neglect tolerance of an individual robot, is defined as the amount of time that the human can neglect, fail to give attention to the robot before the robot's performance drops below a threshold. This in turn determines how many other tasks that the human can manage; high neglect tolerance means that the human can manage many other tasks, and low neglect tolerance means that there is not time to manage much else other than the robot.

In a multi-robot context, the "other tasks" that the human can manage are other semi-autonomous robots that also need human attention. Thus, neglect tolerance determines the maximum number of independent robots that a human can manage [26]. This number of independent robots, called *fan-out*, is typically on the order of one or two to ten or twelve, depending on the types of robots and the tasks that they perform [7].

It is desirable to increase the fan-out so that a human operator can influence hundreds or thousands of robots without encountering unmanageable workload levels. One way to do this is to create robot teams that follow principles of interaction observed in swarms (Figure 1.1) in nature.

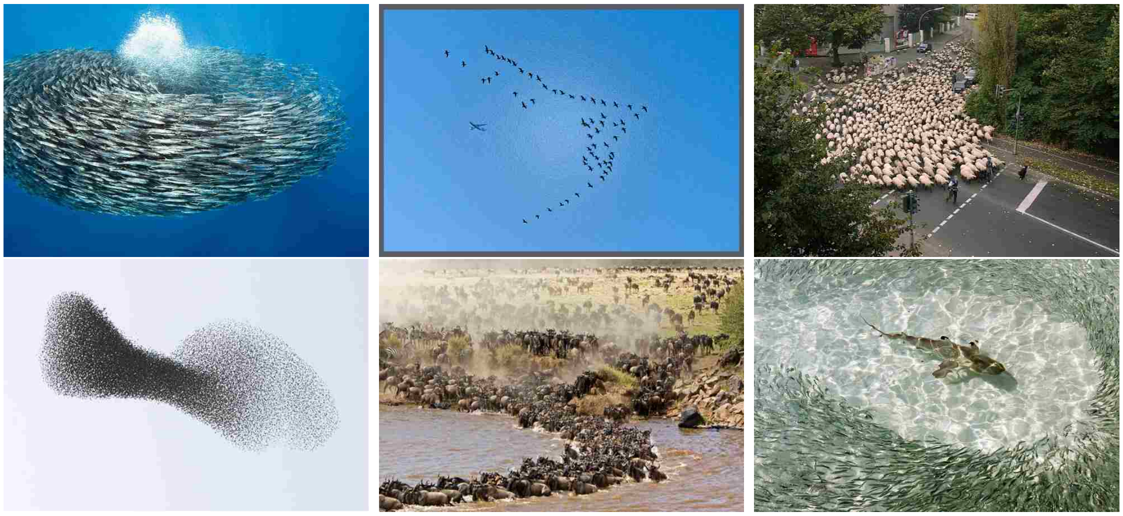
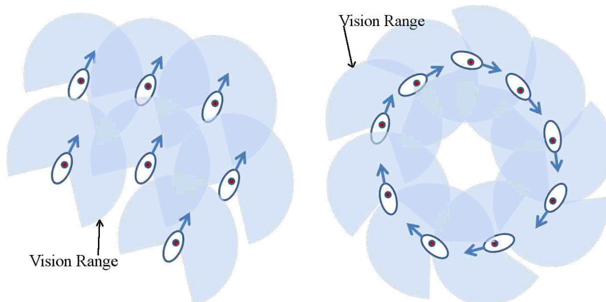


Figure 1.1: Swarms in nature.

Swarm intelligence has received attention from computer scientists since 1989, when Gerado Beni and Jing Wang introduced the expression [3]. A swarm consists of a group of individuals who exhibit collective behaviors. In these swarms, each individual moves without input from a centralized control, responding spontaneously to signals from its environment including its neighbors. Even though there is no leader among the group of individuals, they can exhibit intelligent movements and do meaningful tasks [30].

We can simplify the swarm's behaviors into two general structures: flocking and torus. Flocking is effective for quickly moving a cohesive group of agents to a new location. As shown in Figure 1.2, individuals in a flock are potentially useful for moving a large group of agents from on place to another because all agents head toward the same direction. The flock structure can be applied to search and rescue and mine removal job that requires exploring a broad area. By contrast, a torus structure is potentially useful for tasks that require a group of robots to create a perimeter around a desired location or object. Because agents in a torus move in circular trajectories they provide omnidirectional sensing. For tasks such as military protection and decontamination, a torus structure is often more useful (as illustrated in the chapters that follow) than a flock-like structure. Especially if the torus structure is flexible enough to change its perimeter-shape, it may improves the performance of the tasks.

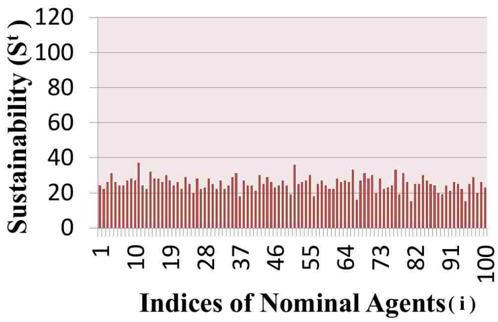


(a) A flock. (b) A torus.

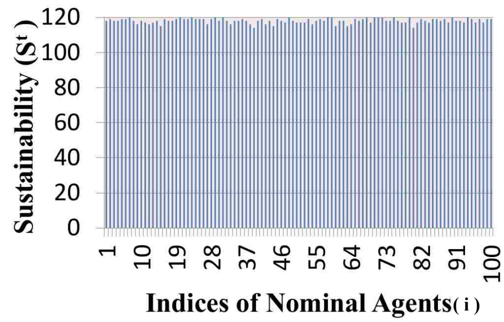
Figure 1.2: A flock and a torus structures of a swarm.

In prior work, researchers have tried to inject human influence into a swarm using metaphors of leaderships or predation, with the goal of solving problems of information foraging, coordinated robot positions, etc. [13, 15, 16, 35]. However, these methods of influence have two main limitations: *(1)* although leaders sustain influence over nominal agents for a long period of time, they tend to cause all collective structures to turn into flocks (essentially negating the potential benefit of the torus structure) [13]; *(2)* predators tend to cause collective structures to fragment, creating a series of small flocks or small tori [13].

This thesis presents a set of new methods for injecting human influence into a swarm. These methods are based on the metaphor of a *mediator*, and result in human-swarm interactions methods that include some of the advantages of both flocking and torus structures. These new models enable a human to maintain influence over swarms by avoiding fragmentation. We provide evidence that these new models allow a human to create torus-like structures that are cohesive and manageable, overcoming the flocking-tendency of leadership and the fragmentation-tendency of predation. To motivate this evidence, consider Figure 1.3, which illustrates how a predator or a leader sustains its influence over nominal agents. To



(a) Previous predation influence over swarms.



(b) Leader influence over swarms.

Figure 1.3: The graphs of a leader and a predator influence over swarms. The x-axis indicates each agent's index, and the y-axis indicates the influence at each time step t (per second)

understand Figure 1.3, let B_i^t be defined as

$$B_i^t = \begin{cases} 1 & \text{if } D_i^t \leq R_{influence} \\ 0 & otherwise \end{cases}$$

where, D_i^t = distance between an agent i and a predator or a leader at time t, $R_{\text{influence}}$ is radius of a predator/leader influence. In other words, B_i^t denotes whether agent i is influenced by a predator or leader at time t. For each agent i, we can evaluate the amount of time that the agent is influenced by the leader or predator. Denote this time as S_i^t, indicating *sustainability*, defined as

$$S_i^t = \sum_{\tau=1}^{t} B_i^\tau. \tag{1.1}$$

Figure 1.3 plots S_i^t for 100 agents ($i \in \{1, 2, \ldots, 100\}$) over a 120 second simulation. The figure illustrates that leaders sustain influence over agents much more effectively than predators.

Since mediators are designed to persistently influence a swarm, a properly design mediator is expected to produce a sustainability graph similar to Figure 1.3(b). Based on results from prior work [13], we hypothesize that a higher sustainability over swarms implies that using the mediators will help an operator better control the swarm.

Our research demonstrates two different direct communications with a swarm: parameter setting and persistent influence. The former method was used to test the behavior of the swarm and the sensitivity of the swarm response to the mediator's behavior. The latter enables real-time communication between an operator and a set of mediators. An operator who is aware of a situation uses an input device such as a keyboard or a mouse to control the mediators. This is the same way an operator communicates with a leader or a predator to control swarms from previous work [9, 12, 13, 29, 36].

1.1 Thesis Statement

Direct influence between a human and a torus-like swarm via mediator agents increases the manageability of a human's influence over swarms compared to leaders and predators. The algorithm for controlling a swarm through mediators have suitable ranges of parameters for swarms, so that it can be used for real robots. Furthermore, multiple mediator agents can be used to control a swarm perimeter into a wide range of shaped tori.

1.2 Overview and Publications

Chapters 2 and 3 of this thesis consist of two published papers. Chapter 2 introduces our proposed models with theoretical analysis of the models. Chapter 3 includes real application of the models and user study results.

Chapter 2 presents experiment setup and result of the robustness of mediator model. The experiment examines the sensitivity and find the range of parameters for stable formation of the model. This chapter also includes the mathematical proof of maximum speed of torus around the mediator. This proof was constructed by Daniel Brown, co-author on the paper, and is not one of the contributions of the thesis.

Chapter 3 is an extension of Chapter 2. This chapter also includes the model description. In addition to that, the chapter includes the experiment design, results of pilot study, and analysis.

The following are citations for the papers that comprise the Chapters 2 and 3.

1. S-Y Jung, D. S. Brown, and M. A. Goodrich. Shaping Couzin-like torus swarms through coordinated mediation. In Proceedings of IEEE International Conference on Systems, Man, and Cybernetics, Manchester, England, To appear 2013.
2. S-Y Jung and M. A. Goodrich. Multi-robot perimeter-shaping through mediator-based swarm control. In Proceedings of IEEE International Conference on Advanced Robotics, Uruguay, To appear 2013.

Chapter 4 includes a more complete evaluation of the results presented in Chapter 3. In order to get better statistical results, we gathered 17 more people to collect data from the user study and observed the similar results to what we analyzed in chapter 3.

Chapter 5 described the result from a physical embodiment of a swarm algorithm. Then, we include conclusions and future work in Chapter 6.

We include a mathematical model of a swarm, user study specifications, generated graphs from the user study, ANOVA test results, and the graph for nodes of robots and environment structures in Robot Operation System in Appendix A, B, C, D, E, and F, respectively.

Chapter 2

Shaping Couzin-like Torus Swarms through Coordinated Mediation

S-Y Jung, D. S. Brown, and M. A. Goodrich. Shaping Couzin-like torus swarms through coordinated mediation. In Proceedings of IEEE Intl. Conf. on Systems, Man, and Cybernetics, Manchester, England, To appear 2013.

Abstract

Human-swarm interaction methods often allow a human to influence a swarm through either leadership or predation. These methods of influence have two main limitations: *(1)* although leaders sustain influence over nominal agents for a long period of time, they tend to cause all collective structures to turn in to flocks (negating the benefit of other swarm formations) and *(2)* predators tend to cause collective structures to fragment. We introduce the use of *mediators* as a novel shared control method for human-swarm influence and use mediators to shape Couzin-like tori [5]. The mediator method uses special agents that operate from within the spatial center of a swarm. This approach allows a human operator to transform and move a dynamic torus formation while sustaining influence over the torus, avoiding fragmentation, and maintaining the torus' connectivity. The use of mediators allows a human to mold and adapt the torus' behavior and structure to a wide range of spatio-temporal tasks such as military protection and decontamination tasks.

2.1 Introduction

A swarm consists of a group of simple individuals who exhibit collective behaviors. In swarms, each individual moves without input from a centralized controller, responding spontaneously to signals from its environment and its neighbors.

A handful of recent flocking and swarming algorithms use three simple heuristic rules [5, 25, 29]: *(1)* each individual attempts to stay within a certain range of its neighbors, *(2)* each individual tries to avoid collisions by maintaining a minimum distance from its neighbors, and *(3)* each individual matches its velocity to its neighbors. Because these simple rules can produce a range of mobile spatial structures, which we call Couzin-like structures, swarms that follow these rules can potentially be applied to many domains such as military force protection, firefighting, search and rescue, etc. [1, 35].

A swarm that is formed by only these simple rules has limited communication, and, consequently, it is non-trivial to shape and guide the way these structures move. One way to allow a swarm to achieve complex goals and adapt to changing environments is to increase the complexity and sophistication of the individual agents. Another way, that minimizes the complexity of individual agents, is to enable a human to influence the swarm, but share control over the swarm's behavior with the individual agents. Enabling human interaction allows swarm algorithms to be flexible in solving complex problems and doing other meaningful tasks such as transporting and collecting objects.

Human influence on swarm intelligence can be categorized as one of four primitive human-swarm interactions [22]. These primitive interactions fall into two different categories of human influence over a swarm: direct and indirect communication [22]. The first way a human can influence a swarm *directly* is by changing agent parameters such as velocity, turning rate, and the zone of influence. For example, changing parameters can cause agents to display different patterns of movement [5, 29]. The second *direct* way is to use persistent influence. This method requires one or more operators who are aware of the current situation and can influence the swarm by giving continuous input[1, 25]. The third *direct* way is through intermittent interactions. This can be done by having the human input goals that the swarm needs to achieve. By using these direct communication methods, a human can control many aspects of swarm behaviors. By contrast, a human can also influence a swarm's behavior *indirectly* by changing features of the environment. This can be accomplished, for example, by an operator who sets up a beacon in the environment to influence how a swarm will move[20, 34].

We introduce a novel way to control a swarm by applying persistent influence via direct communication with agents called *mediators*. We explore two types of mediators. One mediator type repels agents similar to the way a predator does [13, 36]. We show that (a) setting the parameters of individual agents allows these agents to maintain a certain distance from the predator-based mediator and (b) the agents can be made to exhibit encircling motions around the mediators. The other mediator type has the same influence zones as previous leader models [6, 13, 36], but also includes a repulsion region within the attraction region. This mediator type allows a human to alter the collective shape exhibited by agents as they encircle a group of mediators. We provide details about these models later in this paper.

Existing swarm models are typically capable of either flocking [19, 25, 29] or torus behavior [21, 24], and in some cases can exhibit multiple group behaviors depending on the model parameters used [5, 31]. Flocking is effective for quickly moving a cohesive group of agents to a new location. Individuals in a flock can monitor only the front area because all agents head toward the same direction. Conversely, the torus is effective for performing stationary tasks or creating a perimeter. Because agents in a torus move in circular trajectories they provide omnidirectional sensing. This paper focuses on controlling a torus using mediators so that the swarm can travel and change shape while staying cohesive and not changing individual agents' parameters.

2.2 Related Work

Previous work on Human Swarm Interaction (HSI) has described several different methods for controlling the agents in a swarm. Kira and Potter used virtual leaders to influence a swarm [19]. Similar to their control method, Olfati-Saber also used a virtual leader to control the behavior of a flock [25]. Su et al. proposed a method for controlling a flock using multiple virtual leaders where agents have limited sensing capabilities [32]. Mabrouk et al. use a virtual leader to escape from a local minima in a reactive problem domain [23]. While these papers deal with enabling human interaction with swarms through virtual leaders, our approach adds human interaction to a swarm through one or more physical agents that attract and repel agents to shape and steer a torus.

Prior work on exerting human influence over swarms by either leadership or predation has illustrated two limitations: *(1)* although leaders sustain influence over nominal agents for a long period of time, they tend to cause all collective structures to turn in to flocks (essentially negating the potential benefit of the torus formation) [13]; *(2)* predators tend to cause collective structures to fragment, creating a series of small flocks or small tori [13]. We propose a class of mediator agents that allow a human to sustain influence over a torus, change its shape, and move the torus while keeping it intact.

Elkaim and Kelbley showed formation shapes that are similar to those that we propose. They used virtual leaders with attraction potential forces [11]. The basic concept of their approach is to maintain an equilibrium between inter-agent potential forces and the forces applied by a virtual leader positioned at the centroid of the agents. The difference between their model and our model is that our mediator model uses both repelling and attracting forces and keeps these forces constant, whereas their leader agents influence other agents using only a scaled attraction force.

Varghese and McKee manipulate agent position by calculating a geometric transformation that makes each agent move to the right position while avoiding collisions with obstacles [33]. Kawashima et al. investigate the responsiveness of fixed-communication leader-follower networks for manipulating multi-agent formations [18]. Our model does not require calculating a geometric transformation or fixed communication topology, but instead, agents move based on three simple rules and are able to form various formations through the influence of mediators.

2.3 The Model

Figure 2.1: Predators with agents in nature.

The model we propose is biomimetic, meaning biologically inspired [5]. Figure 2.1 shows how agents in nature respond to either their neighbors or to predators, producing round empty space around the predators. Based on this natural behavior, we propose two different agent types: nominal agents and mediators. Mediators are directly influenced by the human, but the nominal agents are influenced indirectly via mediators. This means that the human and nominal agents share control over the specific structure of the swarm because the human can influence nominal agents only by appropriately managing mediators.

We adopt a switching-based control model in which the nominal agents either (a) react to their neighbors or (b) react to the mediators; see Figure 2.2. This gives shared control between a human and a swarm. The human provides input to the mediators, and the mediators influence nominal agents that are within range of the mediators. Since the nominal agents may move in and out of the sensing range of the mediator, agents can switch back

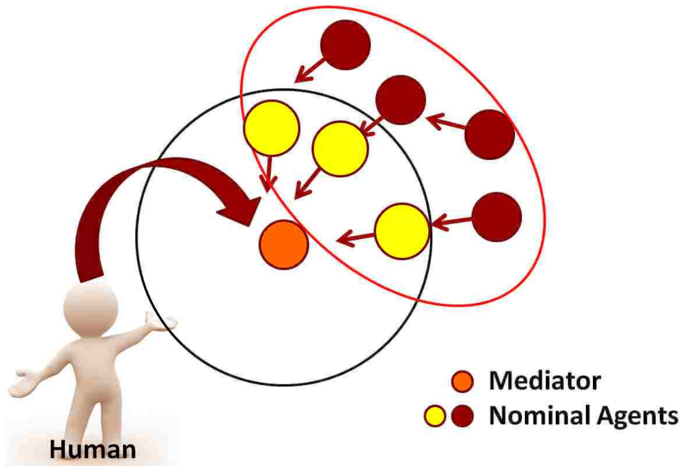


Figure 2.2: Switching-based control model.

and forth between inter-agent influence and mediator influence. Because avoiding collisions is critical, we also added a switch in which nominal agents ignore mediators if inter-agent distance drops below a threshold.

2.3.1 Nominal Agent

The nominal agent uses a two-dimensional implementation of Couzin's three dimensional model as shown in Figure 2.3 [5]. Since we are interested in ground robots, the two-dimensional model is sufficient. As mentioned previously, this model uses three basic rules and can produce two fundamentally different structures: a torus and a flock [5, 29]. The first rule is that each agent attempts to stay close to other agents. This is accomplished by the zone of attraction (R^{att}). Agents attract to neighbors within the zone of attraction to maintain swarm connectivity. The second rule is that each agent tries to avoid collisions with other agents by maintaining a minimum inter-agent distance. This is accomplished by the zone of repulsion (R^{rep}). This rule has the highest priority [5]. This means that an agent will ignore attraction and orientation forces in order to avoid a neighbor within its zone of repulsion. The third rule is that each agent matches its velocity and direction with its neighbors. This is accomplished by the zone of orientation (R^{ori}).

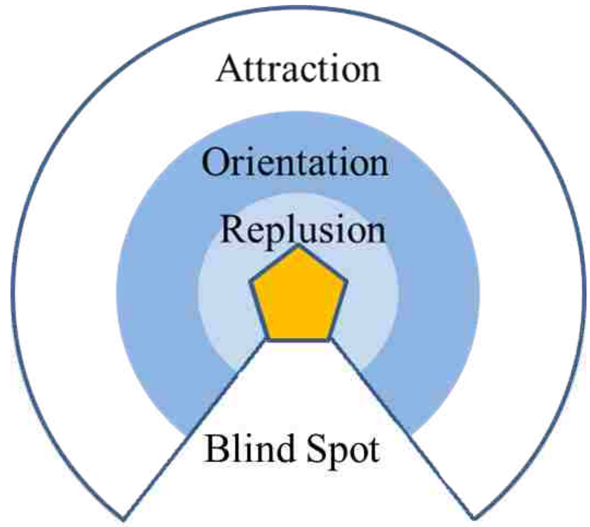


Figure 2.3: The agents zones of influences and sight.

2.3.2 Mediators

In the previous section, we reviewed how nominal agents determine their behavior through inter-agent zones of repulsion, orientation, and attraction. We also indicated that these nominal agents change their behavior when they are in proximity to a mediator, ignoring all inter-agent influences except repulsion and responding only to the mediator.

This means that nominal agents need two sets of parameters for determining their actions: a set of parameters for when they are in the presence of a mediator, and a set of parameters for when they are not in the presence of a mediator. It is useful to treat the former set as a property of the mediator rather than the nominal agent. This allows us to systematically explore how nominal agents respond to different types of mediators.

Mediators exert two forms of influence over the nominal agents: leadership and predation. For the purpose of this paper, *leadership* means the mediators exert attractive influence over nominal agents, pulling nominal agents toward them. Conversely, *predation* means the mediators exert a repelling influence over nominal agents, pushing nominal agents away from themselves.

The first type of mediator, which we call an R-mediator for *repulsion mediator*, influences nominal agents using only predation, but uses what we can call a "weak" form of predation. Weak predation means the mediator repels nominal agents, but the zone of mediator predation is smaller than the zone of nominal attraction. Let the zone of predation be denoted by R^{pred}. Weak predation occurs when $2 \times R^{pred} < R^{att}$, or equivalently $R^{pred} < R^{att}/2$, which means that the range of influence between nominal agents exceeds the maximum range of R-mediator influence on the nominal agents. This allows nominal agents to stay in a cohesive torus formation when a mediator is in the center of the group. Combining this constraint with parameters that Couzin used to produce a torus yields the following ordering of parameters:

$$R^{rep} \; \leq \; R^{ori} \; < \; R^{pred} \; < \; R^{att}/\,2. \tag{2.1}$$

This allows a mediator to be in the middle of a torus and "steer" the torus in various directions, as shown in Figure 2.4.

Figure 2.4: Torus behavior around the mediator.

Note that this means that the nominal agents use the attraction, orientation, and repulsion behaviors identified in the previous section when not in the presence of a mediator;

when a mediator is nearby, the mediator repels the agents and the agents ignore each other except when avoiding collisions.

There are some limitations to this form of mediator-based influence. First, it is difficult to place the mediator into the center of a swarm once the structure is broken. Additionally, if there are not enough nominal agents, the torus behavior of a swarm around the mediator becomes fragmented because the nominal agents don't have enough attractive influence from other nominal agents to stay within a certain range of the mediator.

To overcome these limitations, we introduce an alternative mediator, called an RA-mediator for *repulsion and attraction mediator*. The RA-mediator uses a zone of leadership wherein the mediator attracts the nominal agents. As mentioned above, when a leader agent uses attraction only, it tends to cause all collective structures to turn into flocks. To avoid this, we require the RA-mediator to include both attraction, corresponding to a zone of leadership denoted by R^{lead}, and repulsion, corresponding to a zone of predation denoted by R^{pred}.

Because mediators operate from within the "hole" of the torus, we note that the following parameter ordering allows the mediator to control the behavior of the torus:

$$R^{rep} \leq R^{ori} < R^{pred} < R^{att} < R^{lead}. \tag{2.2}$$

Setting $R^{pred} < R^{att} < R^{lead}$ creates a buffer zone around the mediator, allowing agents to stay close to the mediator but not too close.

Table 2.1 shows how the parameters of the R- and RA-mediators relate to previous work using leaders and predators [13]. The first two rows in the table indicate the parameters used in prior models, and the last two rows indicate parameters for the two types of mediators introduced in this paper.

Using these two different models for mediators, we simulated different forms of human interaction and analyzed the sensitivity of each model to human influence. Before we present

Influencer		Order of Nominal Agent's Each Zone
Leader		$R^{rep} \leq R^{ori} < R^{att} < R^{lead}$
Predator		$R^{rep} \leq R^{ori} < R^{att} < R^{pred}$
Mediator	R	$R^{rep} \leq R^{ori} < R^{pred} < R^{att}/\ 2$
	RA	$R^{rep} \leq R^{ori} < R^{pred} < R^{att} < R^{lead}$

Table 2.1: How nominal agents are influenced. Top two influencers indicate previous models.

our simulation results, we first derive a theoretical result for the maximum speed of a moving torus formation in terms of the nominal agent speed.

2.4 Maximum Speed of a Torus

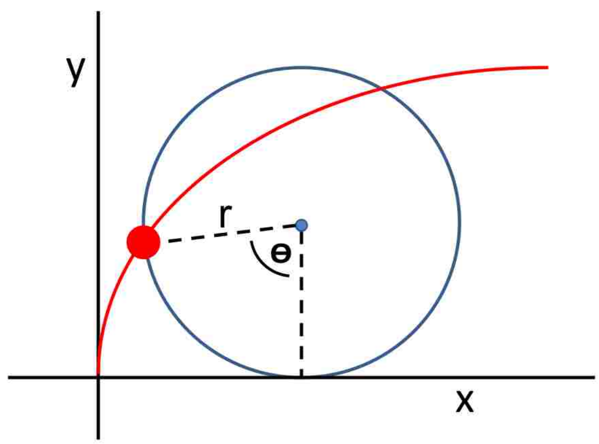


Figure 2.5: Trajectory of an agent represented as a cycloid generated by a circle of radius r that has rotated through the angle θ.

We can think of the torus formation as a rotating disc of radius r. If we consider one agent moving along the perimeter of the torus and if we assume the torus is itself moving (i.e. the centroid of the torus has a certain velocity) then we can think of an individual agent's trajectory as the cycloid shown in Figure 2.5. The parametric equations that govern the motion of a cycloid generated by a circle of radius r and parameterized by θ, the angle through which the rolling circle has rotated, are $x = r(\theta - \sin\theta), \quad y = r(1 - \cos\theta)$. To determine the distance that the agent travels we can calculate the length of the parametric curve, denoted by L, where

$$L = \int_a^b \sqrt{\left(\frac{dx}{d\theta}\right)^2 + \left(\frac{dy}{d\theta}\right)^2}\ d\theta. \tag{2.3}$$

So, the length of one arch of the cycloid is

$$L = \int_0^{2\pi} \sqrt{(r(1-\cos\theta))^2 + (r\sin\theta)^2}\ d\theta = 8r.$$

Assuming that the agent has a speed of s units per second, we want to find the speed of the centroid of the torus, s_{torus}. The time taken for the agent to traverse the arc length is $8r/s$. The center of the disc, or centroid of the torus, has traveled $2\pi r$ units, therefore

$$\max(s_{torus}) = \frac{2\pi r}{8r/s} = \frac{\pi}{4}s. \tag{2.4}$$

Thus, the upper limit on the speed of a torus is approximately three-fourths the speed of an individual agent. Applying this theoretical result to the notion of nominal agents and mediators provides us with a way to calculate the maximum speed of a mediator given a fixed nominal agent speed. If the mediator moves faster than this maximum speed, the nominal agents will not be able to stay in a cohesive torus formation. Alternatively, given a fixed mediator speed, we can calculate the minimum nominal agent speed required to keep the torus cohesive.

2.5 Sensitiviy Analysis

We ran a series of experiments to analyze the sensitivity and robustness of human-swarm interactions through the use of mediators. We investigated different combinations of parameter settings to determine conditions for stable swarm formations. The parameters for a nominal agent are the ranges of zones of attraction (R^{att}), repulsion (R^{rep}), orientation (R^{ori}), as well as speed (s), turning rate (ω), and vision range (θ). The parameters for mediators are the range of predation (R^{pred}), the range of mediator-attraction (R^{lead}), and speed (s^m).

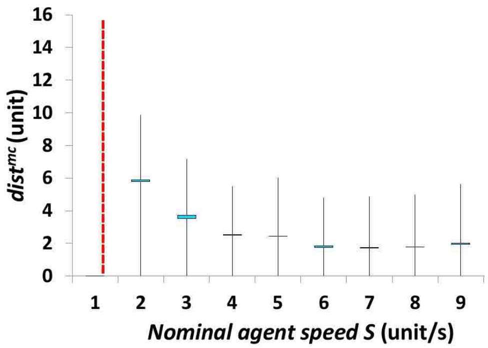
We measured distances in terms of *units* where R^{rep} is fixed as 1 *unit* because it is the minimum distance that is required to avoid collisions. Furthermore, we adopted Couzin's model parameters for vision range (θ) and turning rate (ω) (namely, $\theta = 270°$ and $\omega = 40°/sec$) to ensure that the nominal agents exhibit the same collective behaviors as Couzin's model when not under the influence of a mediator. We also set the number of agents $(N) = 70$ and $R^{pred} = 14$. The other parameters for both nominal and mediator agents were varied.

In the following experiments, the goal is for the mediator to guide the torus through a series of four waypoints, returning to the starting location at the end of the circuit. Each waypoint is each vertex of 80 x 80 unit square. The objective is to find parameter ranges that afford stable human-influenced movement of a torus through mediators.

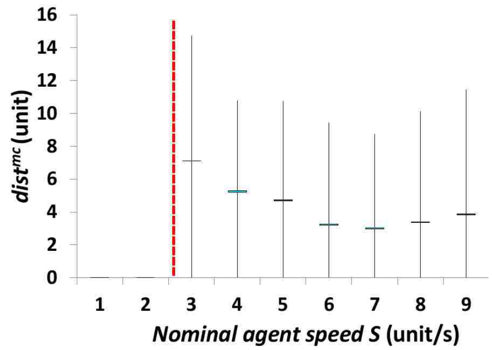
To determine whether the torus remained stable during simulations, we checked two conditions: *nominal-connectivity* and *mediator-controllability*. Nominal-connectivity is a condition that allows us to determine whether nominal agents are connected to each other. Mediator-controllability is a condition on the distance from the swarm-centroid to the mediator, allowing us to determine whether the mediator is in the center of the swarm and can effectively influence the agents.

The nominal-connectivity condition is $\sum_{k=1}^{N} A_{ij}^{k} \neq 0 \quad \forall i, j$ where A is the $N \times N$ adjacency matrix, N is the number of agents, and i and j are agent indices. The centroid of a swarm C is calculated as $C = \frac{1}{N} \sum_{i=0}^{N} P_i$ where P_i is position of agent i. The distance from the swarm-centroid to the mediator is $dist^{mc} = \|P_m - C\|$ where P_m is the position of the mediator. The mediator-controllable condition is $dist^{mc} < R^{pred}$.

Simulation results show that R^{att}, R^{ori}, and R^{lead} do not have much effect on the average distance from the mediator to the swarm's centroid. We also varied the speed of the mediator, s^m, and the speed of the nominal agents, s, and found that these also have little effect on the average difference between the swarm-centroid and the position of the mediator.



(a) Mediator speed $s^m = 1\ unit/s$



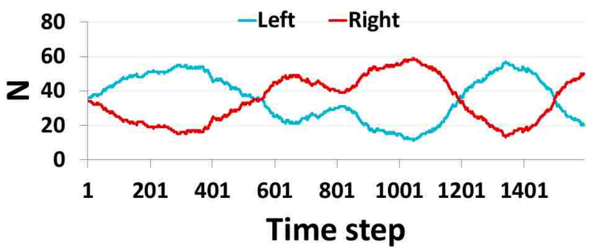
(b) Mediator speed $s^m = 2\ unit/s$

Figure 2.6: Distance from the swarm-centroid to an R-mediator as a function of nominal agents' speed. Each line indicates the minimum and maximum distance from the swarm-centroid to the R-mediator. The upper bound of the box is the mean, and the lower bound of the box is the median. The dashed-line is the minimum speed of the nominal agents, derived from Eq. 2.4. The results for an RA-mediator were similar.

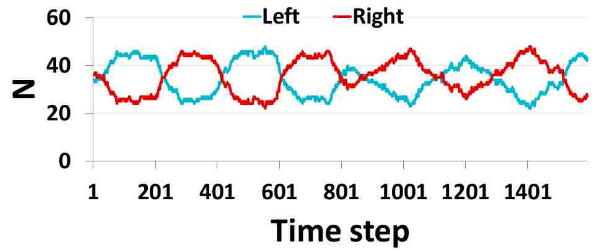
However, as shown in Figure 2.6, as the speed of a nominal agent is increased, $dist^{mc}$ tends to decrease and then stay relatively constant. We also observed that the position of the nominal agents tended to be lopsided if the speed of the nominal agents is not fast enough to follow the mediator.

To further investigate this phenomenon, we kept track of the number of nominal agents on the left and right side of a moving mediator. In these simulations, the mediator starts moving to the right. After about 801 time steps, the mediator turns around and moves to the left. We fixed the speed of mediator to $s^m = 1$ and varied the speed of the nominal agents. As shown in Figure 2.7, if nominal agents move faster, their positions are almost evenly distributed around the mediator. By contrast, if the nominal agents move slower, their positions are lopsided to either the left or right side of the mediator.

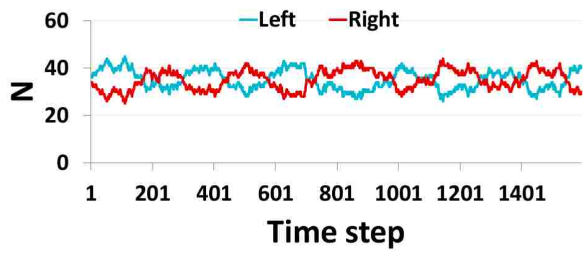
These simulation results show that given a certain mediator speed, if the nominal agents move faster, the mediator will be more likely to stay in the middle of the torus. These



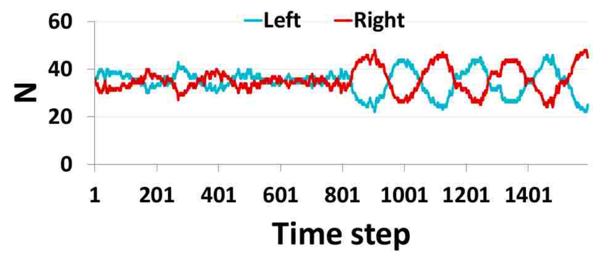
(a) $s = 2\ unit/s$



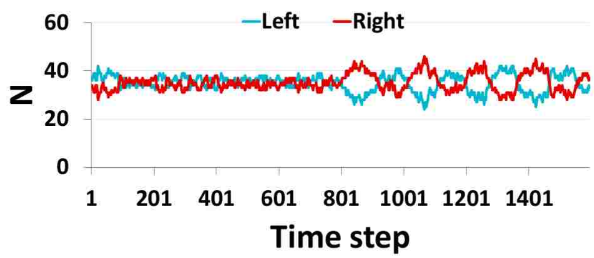
(b) $s = 3\ unit/s$



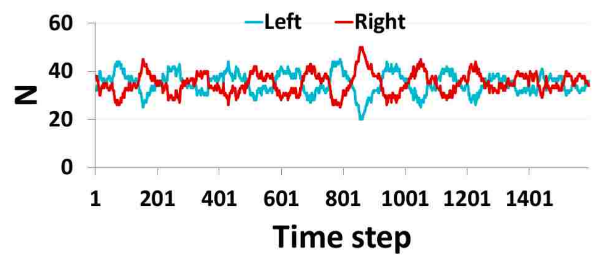
(c) $s = 4\ unit/s$



(d) $s = 5\ unit/s$



(e) $s = 6\ unit/s$



(f) $s = 7\ unit/s$

Figure 2.7: These graphs display the change of the number of nominal agents at a mediator's right and left side. After around 801 time steps, the number of nominal agents at each side fluctuates because the mediator changes its direction to left from right.

results agree with the theoretical results of Section 2.4 where we showed that the speed of the individual agents must be sufficiently faster than the speed of the centroid.

Based on the foregoing experiments, we were able to find suitable ranges of parameters for the nominal agent that afforded robust human influence via a single mediator (see Table 2.2). Note that the parameters are constrained based on Table 2.1. We also observed that the suitable speed of a mediator s^m is restricted by the speed of a nominal agent s. As shown in Figure 2.6 and Section 2.4, torus behavior around a mediator appears when $s^m \leq \frac{\pi}{4}s$. When $s^m \geq 3$, we need to increase the turning rate for the nominal agents to prevent the torus from

	Parameters		
Influencer	R^{ori}	R^{att}	R^{lead}
R-Mediator	1 - 7	31 - 35	-
RA-Mediator	1 - 7	23 - 30	25 - 35

Table 2.2: Summary of nominal agents parameter based on their influencer.

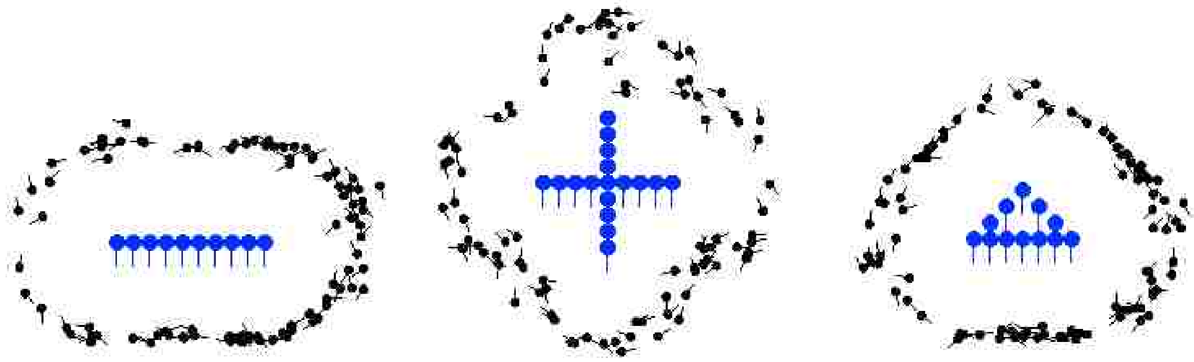


Figure 2.8: Tori Shapes.

fragmenting. Thus, the suitable speed of the mediator is 0–2 $units/s$ when ω is restricted to $40^{\circ}/sec$.

2.6 Shaping Swarms

If we place more than one mediator in the center of a swarm, we can make the nominal agents track many different perimeter shapes. If multiple mediators are given a specific initial configuration and move with the same direction and the same speed, the shape of the swarm is approximately static as the group translates to a new location. Figure 2.8 shows how a group of mediators can manipulate the shape of a swarm. Also, the shape of a swarm can be changed dynamically by the human operator by moving the mediators. For example, the bar shape can be transformed into triangle or many other desired shapes.

To extend this idea further, we introduce a new type of nominal agent, which we call the *smart agent*. Smart agents, or S-agents, are inspired by the behavior of the sheep illustrated in Figure 2.9. In this figure, the sheep are orbiting a moving car. Because the car

Figure 2.9: Sheep's encircling motion around a car.

covers part of the sheep's vision, the sheep cannot see the entire group's movement. Rather, they can see only the neighbors in front of them so they follow those neighbors.

Likewise, if S-agent i in a swarm observes a set of neighbors O, it decides to follow the closest neighbor E_i where

$$E_i = \underset{j \in O}{\operatorname{argmin}}(\sqrt{(i_x - j_x)^2 + (i_y - j_y)^2}). \tag{2.5}$$

This corresponds to a nearest neighbor topology which has been shown to accurately model interactions in natural flocks [2]. The main difference between an S-agent and a nominal agent is that an S-agent has a more narrow field of view ($\theta = 180°$ rather than $270°$). Because an S-agent has a larger blind spot, it needs more than just attraction to maintain the connectivity of the swarm.

In order to make the agents "smarter", each agent i remembers the last location of its closest neighbor, P_{E_i}. When an S-agent does not observe any neighbors within its vision, the S-agent recalls the last location of its closest neighbor and moves towards that location. As soon as the S-agent observes a neighbor, it responds to the observed neighbor and resets its memory.

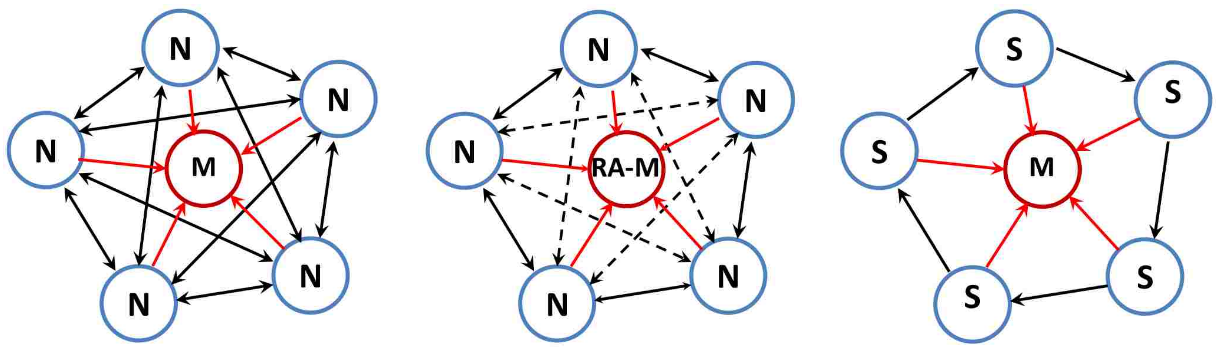


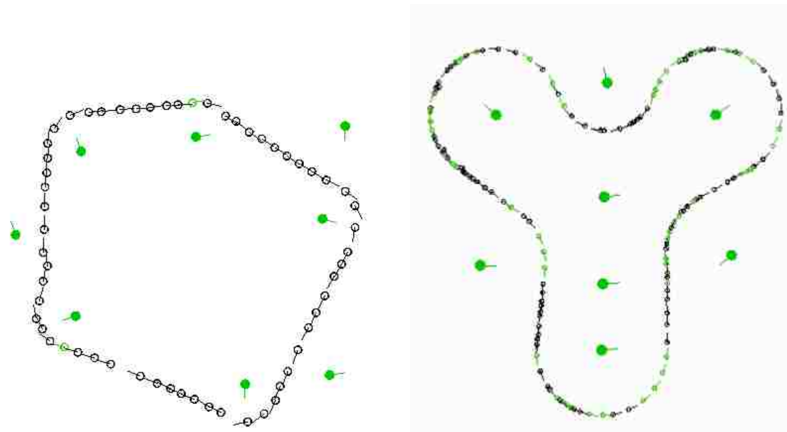
Figure 2.10: Topologies among nominal agents N, S-agents S, and mediators R- and RA-M. Black lines indicate the response among nominal agents. Dashed-lines indicate that nominal agents may respond to each other depending on the range of influence. Red lines indicate the response to the mediator. The notation $a \rightarrow b$ means a is influenced by b.

Another way of being smarter so as to maintain connectivity is that each S-agent has the ability to increase its speed when it gets far from its nearest neighbor [4]. The speed for agent i is

$$s_i(t+1) = \begin{cases} \gamma \times s & \text{if } \|P_i - P_{E_i}\| > \mathit{Stable\ Dist} \\ s & \mathit{otherwise} \end{cases} \tag{2.6}$$

where s is constant and $\gamma > 1$ determines how much the agent increases its speed. Using the same simulation setup as in Section 2.5, we found that when $\mathit{Stable\ Dist} \leq 0.9 \times R^{att}$ and $\gamma \geq 1.1$, the torus remained stable during the simulations. Also, we found that the mediator needs to move slower with S-agents than with nominal agents to maintain a stable torus formation.

Figure 2.10 shows the different topologies that result when using mediators with either nominal agents or S-agents. Nominal agents show more influence dependencies than S-agents. This means that nominal agents respond to more neighbors than S-agents do in order to maintain their connectivity—S-agents need only the closest neighbor in front of them. Consequently, using S-agents slides the weight of shared control from being highly weighted



(a) (b)

Figure 2.11: Dynamic transformation of S-agents from an amorphous blob (a) to a Y shape (b) under the influence of a group of coordinating R-mediators.

on nominal agents to being equally weighted between mediators and S-agents. Because of this change, S-agents are better suited to shaping swarms than nominal agents.

Figure 2.11 illustrates that a group of S-agents under the influence of a group of R-mediators can adopt a set of very flexible shapes, more than is possible with nominal agents under the influence of a group of mediators. This preliminary observation is encouraging for two reasons. First, unlike prior work on predator-based or leader-based influence, mediators allow us to manage agents in a torus shape. Second, we can "warp and bend" the shape of the torus by a proper positioning of mediators.

2.7 Conclusion and Future Work

We introduced a new shared control model for human-swarm interaction using mediators and demonstrated that this model can be used to transform a swarm into a variety of shapes. Because mediator-based swarm control allows a swarm to maintain a torus formation while it is moving, the swarm retains the advantages of torus behavior, in contrast to previous work on leader and predator based control. We also analyzed the sensitivity of this model and found that there is a wide range of parameters for both nominal agents and mediators that allow a mediator to stay in the middle of a stable moving torus. In future work, we will study whether mediated swarms can be robustly applied in the noisy conditions which will exist with real robots. Because individual agents in our model use constant speed and limited turning rates—which is similar to Dubins path algorithm commonly used for robot path planning [10]—we hope to apply our mediator model to real robots in the future. Future work will also examine how robustly the mediator model can handle a variety of shapes.

Acknowledgment

We would like to thank the Science of Autonomy program of the Office of Naval Research for funding this work. The opinions of this paper do not necessarily reflect the funding agency.

Chapter 3

Multi-Robot Perimeter-Shaping through Mediator-Based Swarm Control

S-Y Jung and M. A. Goodrich. Multi-robot perimeter-shaping through mediator-based swarm control. In Proceedings of IEEE Intl. Conf. on Advanced Robotics, Uruguay, To appear 2013.

Abstract

A swarm is a group of uninformed individuals that exhibit collective behaviors. The group without any information has limited ability to achieve complex goals. Human-swarm interaction methods often allow a human to influence these uninformed individuals through either leadership or predation as informed agents that directly interact with humans. These methods of influence have two main limitations: *(1)* although leaders sustain influence over nominal agents for a long period of time, they tend to cause all collective structures to turn in to flocks (negating the benefit of other swarm formations) and *(2)* predators tend to cause collective structures to fragment. In this paper, we present the use of *mediators* as a novel form for human-swarm influence and use mediators to shape the perimeter of a swarm. The mediator method uses special agents that operate from within the spatial center of a swarm. This approach allows a human operator to coordinate multiple mediators to modulate a rotating torus into various shapes while sustaining influence over the swarm, avoiding fragmentation, and maintaining the swarm's connectivity. The use of mediators allows a human to mold and adapt the torus' behavior and structure to a wide range of spatio-temporal tasks such as military protection and decontamination tasks. This paper also provides the results of the experiment concerned with decontamination task that compares

previous informed agent methods to the mediator-based control with regard to manageability and performance.

3.1 Introduction

Performing tasks with multiple robots potentially increases the performance and flexibility of robots, but at a cost of increased difficulty for the human(s) responsible for managing the robots. To manage multiple robots efficiently, many researchers have tried to find an efficient control method by observing swarm behavior in nature. In this work, a swarm consists of a group of simple individuals who act without input from a centralized controller, responding spontaneously to signals from its environment and its neighbors.

In this paper, we utilize a swarm model in which each individual in the swarm follows three simple heuristic rules [5, 25, 29]: *(1)* each individual attempts to stay within a certain range of its neighbors, *(2)* each individual tries to avoid collisions by maintaining a minimum distance from its neighbors, and *(3)* each individual matches its velocity to its neighbors. Swarms that follow these rules can exhibit a range of mobile spatial structures including simple flocking and torus behaviors similar to what have been observed in nature for groups of birds or fish. Although there are a range of collective structures that can be produced by these simple rules, we focus on a torus structure, partly because of its usefulness and partly because it has received less attention in the literature than other swarm structures.

A swarm that is formed by only these simple rules has limited information and, consequently, it is hard to shape and guide the way the resulting swarm structures move. One way to allow a swarm to achieve complex goals and adapt to changing environments is to increase the complexity and sophistication of the individual agents. Another way, which minimizes the complexity of individual agents, is to enable a human to interact with the swarm. Both approaches have been used in the literature and have been applied to important problems such as military force protection, firefighting, search and rescue, etc. [1, 35].

In this paper, we adopt the latter approach and influence swarm behavior by placing informed agents among uninformed agents. The informed agents directly respond to an operator's input, and the uninformed agents respond to the informed agents. In this way, a human can use direct influence over a handful of robots to control an entire swarm.

We introduce a novel way to control a swarm by applying persistent influence with a new type of informed agents called *mediators*. The special types of mediators that we describe below repel uninformed agents similar to the way a predator does [13, 36] but use parameters that cause the uninformed agents to "stay close but not too close" to the mediators. This approach allows a human to alter the collective shape exhibited by agents as they encircle a group of mediators. In addition, the mediator-based control increases the manageability of a human's influence over swarms compared to leaders and predators. We investigate these claims about swarm manageability and performance using a study of a decontamination task with three different approaches to informed agent-based control.

3.2 Related Work

Previous work on Human Swarm Interaction (HSI) has described several different methods for controlling the agents in a swarm. Kira and Potter used virtual leaders to influence a swarm [19]. Similar to their control method, Olfati-Saber also used a virtual leader to control the behavior of a flock [25]. Su et al. proposed a method for controlling a flock using multiple virtual leaders where agents have limited sensing capabilities [32]. Mabrouk et al. use a virtual leader to escape from a local minima in a reactive problem domain [23]. While these papers deal with enabling human interaction with swarms through virtual leaders, our approach adds human interaction to a swarm through one or more informed agents that simultaneously attract and repel uninformed agents to shape and steer a torus.

Elkaim and Kelbley showed formation shapes that are similar to those that we propose. They used virtual leaders that exerted attraction on other agents, and allowed obstacles to exert repulsion potential forces on those agents [11]. The basic concept of their approach is to maintain an equilibrium between inter-agent potential forces and the forces applied by a virtual leader positioned at the centroid of the agents. Our approach differs in that it does not account for obstacles and uses mediators that exert only a repulsion force on nominal agents.

Varghese and McKee manipulate agent position by calculating a geometric transformation that makes each agent move to a desired position while avoiding collisions with obstacles [33]. Kawashima et al. investigate the responsiveness of fixed-communication leader-follower networks for manipulating multi-agent formations [18]. Our model does not require calculating a geometric transformation or a fixed communication topology but, instead, agents are able to flexibly form various formations through the influence of mediators.

Kolling et al. present two different ways of enabling human operators to control robot swarms: selection control and beacon control [20]. Selection control allows the operator to select a subset of agents in the swarm and to control consistently. This is a form of direct and intermittent interaction that requires that the operator knows the entire environment. Beacon control is similar to a leader or a predator approach, but one in which the leader/predator doesn't move. This is a form of indirect interaction. In contrast to these approaches, control by mediator agents uses direct interaction and includes both parameter setting and persistent influence.

3.3 The Model

The model we propose is biomimetic, meaning biologically inspired [5]. Figure 3.1 shows how agents in nature simultaneously respond to both their neighbors and to predators, producing round empty spaces around the predators. Inspired by this natural behavior, we propose two different agent types, nominal agents and mediators, and a mechanism for combining these two agent types. Mediators are directly influenced by a human, and nominal agents are influenced directly by mediators. The term *mediator* indicates that the human does not directly influence the nominal agents, but rather indirectly influences nominal agents via the mediators. This means that the human and nominal agents share control over the specific structure of the swarm because the human can influence nominal agents only by appropriately managing mediators.

Figure 3.1: Predators with agents in nature.

We adopt a switching-based control model in which the nominal agents either (a) react to their neighbors or (b) react to the mediators but (c) not both. The human provides input to the mediators, and the mediators influence nominal agents that are within range of the mediators. Since the nominal agents may move in and out of the sensing range of the mediator, agents can switch back and forth between inter-agent influence and mediator influence. Because avoiding collisions is critical, we also added a switch in which nominal agents ignore mediators if inter-agent distance drops below a threshold.

3.3.1 Nominal Agent

A nominal agent is a typical type of an uninformed agent that uses a two-dimensional implementation of Couzin's three dimensional model [5]. Since we are interested in ground robots, the two-dimensional model is sufficient. As mentioned previously, this model uses three basic rules and can produce two fundamentally different structures: a torus and a flock [5, 29]. The first rule is that each agent attempts to stay close to other agents. This is accomplished by the zone of attraction (R^{att}). Agents are attracted to neighbors within the zone of attraction to maintain swarm connectivity. The second rule is that each agent tries to avoid collisions with other agents by maintaining a minimum inter-agent distance. This is accomplished by the zone of repulsion (R^{rep}). This rule has the highest priority [5], meaning an agent ignores attraction and orientation forces in order to avoid a neighbor within its zone of repulsion. The third rule is that each agent matches its velocity and direction with its neighbors. This is accomplished by the zone of orientation (R^{ori}).

In addition to Couzin's rules, we add another rule that dictates how the nominal agents behave when near a mediator. In particular, we assume that when nominal agents are near a mediator they ignore all inter-agent influences except repulsion and respond only to the mediator. This means that nominal agents need two sets of parameters for determining their actions: a set of parameters for when they are in the presence of a mediator, and a set of parameters for when they are not in the presence of a mediator. It is useful to treat the former set as a property of the mediator rather than the nominal agent. This allows us to systematically explore how nominal agents respond to the mediator, which we now explain further.

3.3.2 Mediator

For the purposes of this paper, *leadership* means means that a mediator (called a leader in this case) exerts an attractive influence over uninformed agents, pulling uninformed agents toward them. Conversely, *predation* means the mediator (called a predator in this case) exerts a repelling influence over uninformed agents, pushing uninformed agents away. Thus, we have two specific types of mediators that we refer to as leaders and predators. We now introduce a third type of mediator, which we will call *the* mediator and distinguish it from leaders and predators.

The mediator influences nominal agents using only predation, but uses what we can call a "weak" form of predation. Weak predation means the mediator repels nominal agents, but the zone of mediator predation is smaller than the zone of nominal attraction. Let the zone of predation be denoted by R^{pred}. Weak predation occurs when $2 \times R^{pred} < R^{att}$, or

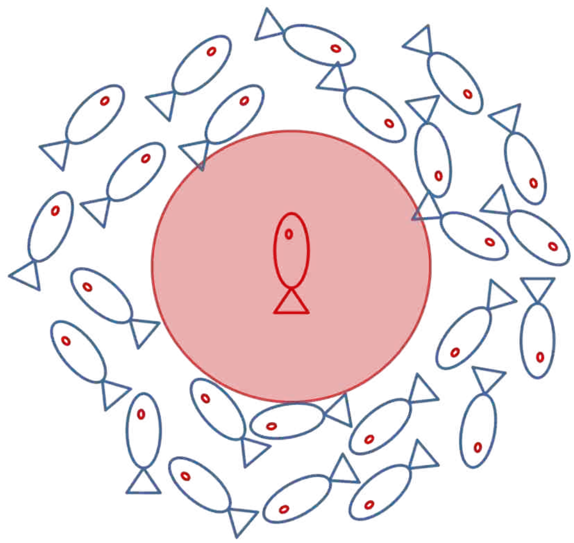


Figure 3.2: Torus behavior around the mediator.

equivalently $R^{pred} < R^{att}/2$, which means that the range of influence between nominal agents exceeds the maximum range of mediator influence on the nominal agents. This allows nominal agents to stay in a cohesive torus formation when a mediator is in the center of the group. Combining this constraint with parameters that Couzin used to produce a torus yields the following ordering of parameters:

$$R^{rep} \;\leq\; R^{ori} \;<\; R^{pred} \;<\; R^{att}/\,2. \tag{3.1}$$

This allows a mediator to be in the middle of a torus and "steer" the torus in various directions, as shown in Figure 3.2.

Note that this means that the nominal agents use the attraction, orientation, and repulsion behaviors identified in the previous section when not in the presence of a mediator; when a mediator is nearby, the mediator repels the agents and the agents ignore each other except when avoiding collisions.

Table 3.1 shows how the parameters of the mediator relate to previous work using a leader and a predator [13]. The first two rows in the table indicate the parameters used in prior models, and the last two rows indicate parameters for the two types of mediators introduced in this paper.

Informed Agent	Order of Nominal Agent's Each Zone
Leader	$R^{rep} \leq R^{ori} < R^{att} < R^{lead}$
Predator	$R^{rep} \leq R^{ori} < R^{att} < R^{pred}$
Mediator	$R^{rep} \leq R^{ori} < R^{pred} < R^{att}/\ 2$

Table 3.1: How nominal agents are influenced. Top two Informed Agent indicate previous models.

3.4 Shaping Swarms

If we place more than one mediator in the center of a swarm, we can make the nominal agents track many different perimeter shapes. Before doing so, we note that a portion of this section and the previous section were first described in our previous work [17]; this paper significantly extends prior work and includes a careful user study with results that were not previously published. If multiple mediators are given a specific initial configuration and move with the same direction and the same speed, the shape of the swarm is approximately static as the group translates to a new location.

In order to create a range of controllable torus shapes, we alter nominal agent behavior to create so-called *smart agents* [17]. Smart agents, or S-agents, are inspired by the behavior of the sheep illustrated in Figure 3.3. In this figure, the sheep are orbiting a moving car. Because the car covers part of the sheep's vision, the sheep cannot see the entire group's movement. Rather, they can see only the neighbors in front of them so they follow those neighbors.

Likewise, if S-agent i in a swarm observes a set of neighbors O, it decides to follow the closest neighbor E_i where

$$E_i = \underset{j \in O}{\operatorname{argmin}}\left(\sqrt{(i_x - j_x)^2 + (i_y - j_y)^2}\right). \tag{3.2}$$

This corresponds to a nearest neighbor topology which has been shown to accurately model interactions in natural flocks [2]. The main difference between an S-agent and a nominal agent is that an S-agent has a more narrow field of view ($\theta = 180°$ rather than $270°$). Because an S-agent has a larger blind spot, it needs more than just attraction to maintain the connectivity of the swarm.

Figure 3.3: Sheep's encircling motion around a car.

In order to make the agents "smarter", each agent i remembers the last location of its closest neighbor, P_{E_i}. When an S-agent does not observe any neighbors within its vision, the S-agent recalls the last location of its closest neighbor and moves towards that location. As soon as the S-agent observes a neighbor, it responds to the observed neighbor and resets its memory.

Another way of being smarter to maintain connectivity is that each S-agent has the ability to increase its speed when it gets far from its nearest neighbor [4]. The speed for agent i is

$$s_i(t+1) = \begin{cases} \gamma \times s & \text{if } \|P_i - P_{E_i}\| > \mathit{Stable\ Dist} \\ s & \mathit{otherwise} \end{cases} \tag{3.3}$$

where s is constant and $\gamma > 1$ determines how much the agent increases its speed. We tested that when $\mathit{Stable\ Dist} \leq 0.9 \times R^{att}$ and $\gamma \geq 1.1$, the torus remained stable during the simulations. Also, we found that the mediator needs to move slower with S-agents than with nominal agents to maintain a stable torus formation.

Figure 3.4 illustrates the different topologies that result when using mediators with either nominal agents or S-agents. Nominal agents show more influence dependencies than S-agents. This means that nominal agents respond to more neighbors than S-agents do in order to maintain their connectivity—S-agents need only the closest neighbor in front of them. As noted in [17], using S-agents slides the weight of control from being highly weighted on nominal agents to being equally weighted between mediators and S-agents. Because of this change, S-agents are better suited to shaping swarms than nominal agents.

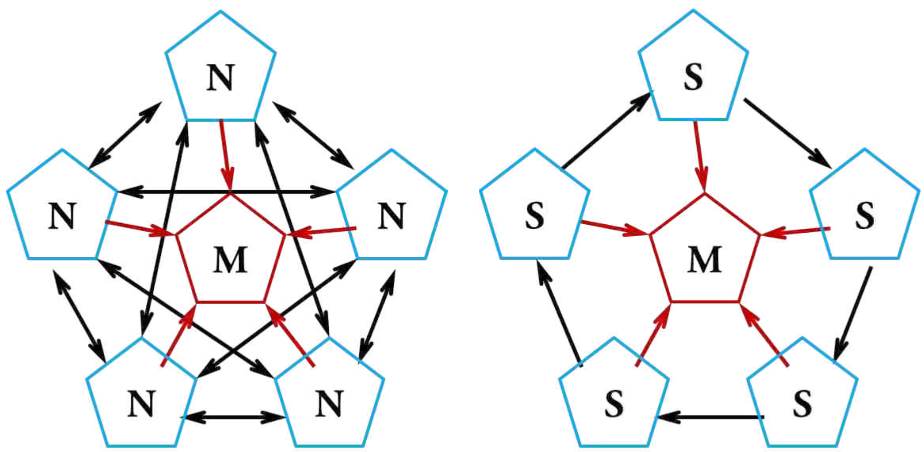
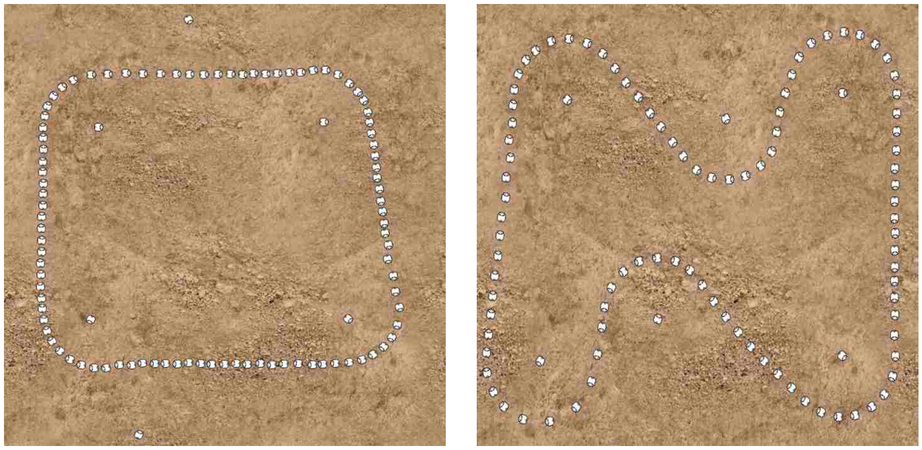


Figure 3.4: Topologies among nominal agents N, S-agents S, and mediators M. Black lines indicate the response among nominal agents. Red lines indicate the response to the mediator. The notation $a \to b$ means a is influenced by b.

Figure 3.5 illustrates that a group of S-agents under the influence of a group of mediators can adopt a set of very flexible shapes, more than is possible with nominal agents under the influence of a group of mediators. The next section presents results from an experiment that illustrate that S-agents can be managed by mediators to perform interesting problems, and do so better than leaders or predators.



(a) (b)

Figure 3.5: Dynamic transformation of S-agents from an amorphous blob (a) to a N shape (b) under the influence of a group of coordinating mediators.

3.5 Experiment Setup

In this paper, we claim that *(a)* mediator-control increases the manageability of swarm control compared to leaders and predators and *(b)* swarm-shaping can be used for a real application. To explore how swarm-shaping can be effectively used in a real world application, we designed an experiment that used a problem that is best performed when multiple robots can be placed in a flexible, dynamic shape around the perimeter of an interesting spatio-temporal problem. This means that task performance needs to be associated with the spatial allocation of robots under time pressure. We created an ocean-based oil spill scenario for the experiment since currents and winds cause the oil spill to take various shapes. This means that the robots need to be able to adopt different shapes to confine the oil contaminants.

We created two scenarios that subjectively have different workloads. This allows us to explore whether advantages of mediator-based control are robust to changes in the problem caused by environmental conditions. The experiment is thus a 2×3 design with two workload levels and three types of informed agent; see Table 3.2.

	Informed Agent		
Scenario	Leader	Predator	Mediator
Low Workload			
High Workload			

Table 3.2: The layout of the case study.

We include seven measurements that reflect two types of measures: manageability and task performance. Measures include both subjective and objective measures of performances. Measures of manageability are as follows:

- **Sustainability**: This is an objective measure of how well a human can sustain average influence over all agents in the collective. High sustainability indicates that it is easier for a human to manage the group. This can be calculated by $S_t = \sum_{i=1}^{t} B_i$ where, S_t = sustainability at time t, n = number of agents, and

$$B_i = \begin{cases} 1 & \text{if } d_i \leq R_{\text{influence}} \\ 0 & \text{otherwise} \end{cases}$$

  where, d_i = distance between an agent i and an informed agent (leader, predator, mediator), $R_{influence}$ = radius of influence zone, B = the adjacency matrix between S-agents and the informed agent.

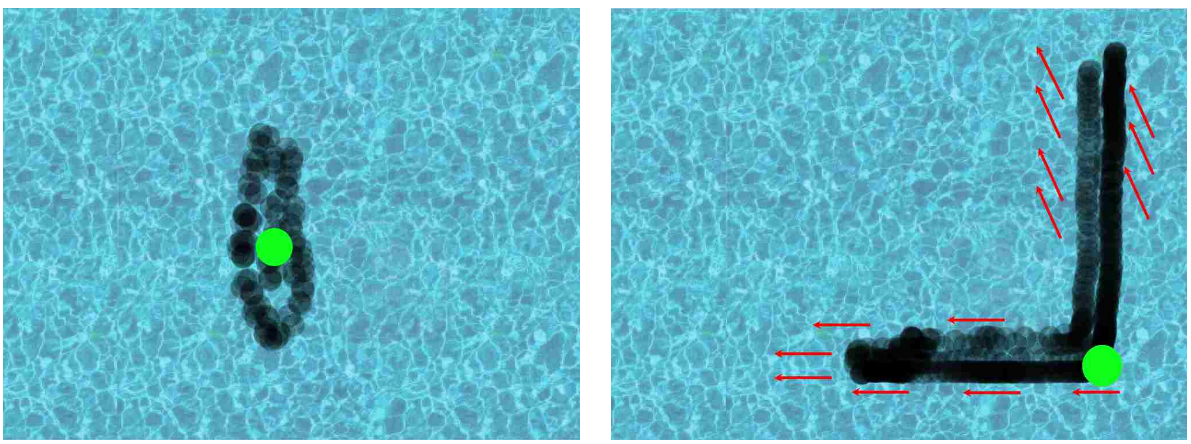
- **NASA-TLX:** This is a subjective measure of the workload required to manage the group.

- **Secondary task performance:** This is a more direct measure of workload, because high error rates indicate that the human is using cognitive resources to manage the robots and has little free capacity.

- **Travel distance:** This indicates how far the informed agents (leader, predator, mediator) had to move, allowing us to infer how much effort the user requires to manage S-agents.

Measures of task performance are as follows:

- **Amount of contaminant removed:** The primary task is to surround a shaped contaminant by a group of agents, so this is a direct measure of performance.
- **Contaminated area:** The task is designed so that users can hypothetically remove the contaminants in three minutes, but this is difficult to do in practice. However, groups that are easy to control and shape should leave less contaminated area.



(a) Low workload scenario map. (b) High workload scenario map.

Figure 3.6: The contaminant source (green dot) produces a new quanta of oil contaminant every two seconds. (a) No ocean currents. (b) Directions of ocean currents are marked as red arrows.

In the experiment, participants were given three minutes to remove as much contaminant as possible. Participants used a mouse and a keyboard to control leaders, predators, or mediators during the scenario. Parameter used in the experiment are shown in Table 3.3. We measured distances in terms of *units* where R^{rep} is fixed as 1 *unit* because it is the minimum distance that is required to avoid collisions. All conditions fixed the influence range of informed agents (leaders, predators, mediators) at 14 units, the number of informed agents at 4, and the number of nominal agents at 100.

	Parameters					
Agent Type	R^{rep}	R^{ori}	R^{att}	$s/unit$	ω ($^\circ/sec$)	θ
Nominal Agent	1	4	20	3	40	270
S-Agent	1	1	20	4	40	180

Table 3.3: Summary of uninformed agents' parameters: speed s, turning rate ω, and vision range θ.

3.6 Mission

Each participant operates each of the different types of informed agents (leader, predator, mediator) to manage and control multiple uninformed agents to form a perimeter around the oil spill and absorb as much oil as possible. As Figure 3.6 shows, one oil source is located in the middle of the oil contaminants and produces a new quanta of oil contaminant every two seconds. Each quanta is repelled by other contaminants and moves depending on ocean currents. If the uninformed agents are near enough to the oil for long enough, the oil is absorbed[1] Encircling a quanta makes the quanta disappear more quickly because encircling optimizes the number of agents within decontamination range.

For the secondary task, participants hear two different sounds: a target bell sound ("ding") and a distractor spring sound ("sproing"). They were instructed to press the space bar when they heard the bell and to do nothing when they heard the spring. Every two seconds, the probability P of a sound playing is drawn from a uniform distribution, $u(0.3, 0.7)$. The probability of a bell sound playing is fixed from the beginning of each scenario and is a Bernoulli random variable R, where $R \sim u(0.55, 0.75)$.

Each participant was assigned to a counterbalanced combination of each scenario and informed agent yielding a within-subjects designs. We recruited 13 participants from the campus of the Brigham Young University, 8 males and 5 females, ranging from 18–32 years old (average 24.23). After completing the informed consent process but before we gathered

[1]Each quanta contains 3000 particles inside a circle of radius 5 units. Particles are absorbed at a rate one particle per simulation time step per agent within 5 units of the circle boundary.

data, every participant was trained to manage the swarms with each type of informed agents in a simplified version of the oil spill problem.

3.7 Results and Discussion

In this section, we address the following two questions: First, does mediator-control method improve the manageability of a robot swarm? Second, does mediator-control method increase the performance of decontamination task? Data was analyzed using a repeated measures ANOVA.

3.7.1 Manageability

Since the probability of playing sounds are random, it is hard to define how well participants did in the secondary task. Thus, we calculated the secondary task score by adding all the number of positive responses and negating the number of negative responses. Then, we normalized the score by the total number of produced sounds. Although averages show that the score for mediators is a little higher than others (see Table 3.4), the ANOVA for the secondary task revealed that there is no significant difference across the scenarios ($F[1, 24] = 0.983,\ p = 0.412$) and among the three informed agents ($F[2, 36] = 0.682,\ p = 0.514$).

For the score of NASA-TLX across the scenarios for predators ($F[1, 24] = 16.616,\ p = 0.002$) and leaders ($F[1, 24] = 7.014,\ p = 0.02$), there are significant differences. However, mediator showed no significant difference ($F[1, 24] = 0.226,\ p = 0.643$) across the scenarios. Fig. 3.7 illustrates that workload increases when using leaders and may actually decrease using predators, but stays relatively flat for mediators. It also shows that the mediator's NASA-TLX score is the lowest.

Based on results from [14], we hypothesized that high sustainability enables a human to manage a swarm easily. However, Table 3.4 shows that the leader has the highest sustainability. On the other hand, the mediator's sustainability is similar to the predator's because when

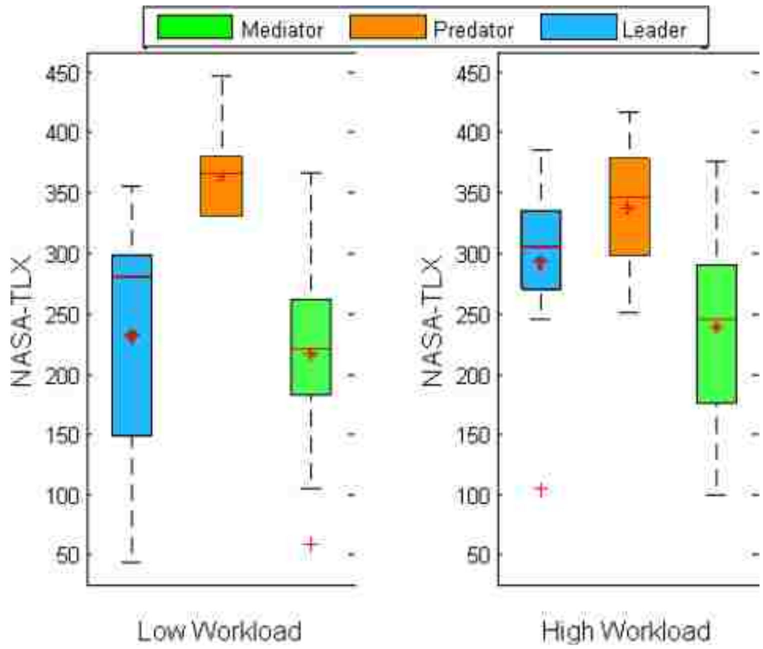


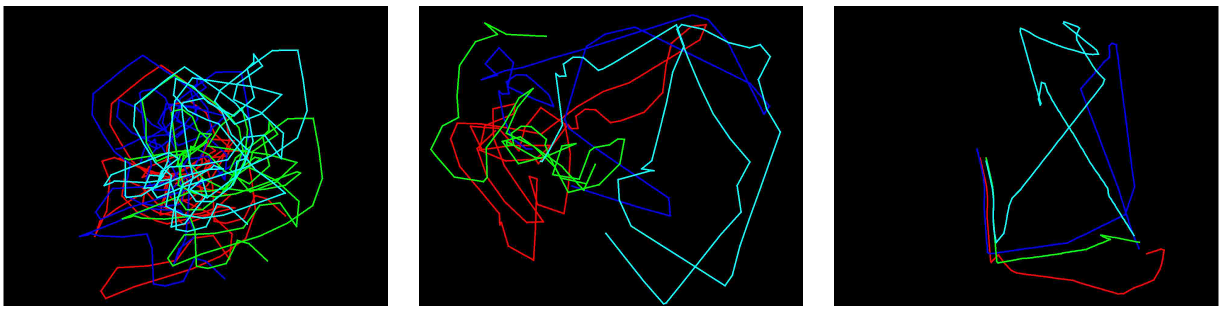
Figure 3.7: NASA-TLX scores

the shape gets bigger, uninformed individual has more chance to interact each other and less chance to interact with mediators. This suggests that sustainability, meaning the total number of uninformed agents influenced by the informed agents, is less important for problems where a swarm must be shaped than for a swarm that must flock to different locations.

	Leader	Predator	Mediator
Secondary task score	1.71	1.69	1.75
Sustainability	176.2	17.92	17.71
Travel Dist.(unit)	889.54	1054.97	249.0

Table 3.4: Qualitative results of secondary task score, sustainability, and travel distance.

However, the total distance traveled by the mediators' is much lower than the distances of other informed agents as shown in Table 3.4. As illustrated in Fig. 3.8, it is easy to see that mediators need to move less to manage the swarm than other two informed agents. This impacts the strategies used to control the uniformed agents. Because leaders facilitate sustainable influence, participants tended to gather all agents in the swarm near the contaminants and then guide this cluster from contaminant to contaminant. For predators, participants tended to turn the swarm into several groups of flocks and tori, which they then "pushed" to different contaminant areas; the predators were then moved around the map to guide the separate groups. Because of this, predators tend to travel a lot. Participants tended to place mediators near the boundaries of the spill and then move the mediators toward the source of the spill as contaminants were removed, resulting in little travel distance.



(a) Leaders (b) Predators (c) Mediators

Figure 3.8: Trajectories of informed agents.

In summary, lower NASA-TLX scores and lower distances travel suggest that mediator-based control is easier for humans.

3.7.2 Performance

As shown in Fig. 3.9, both leader-based control ($F[1, 24] = 4.457,\ p = 0.06$) and predator-based control ($F[1, 24] = 1.615,\ p = 0.23$) do not show significant differences in the amount of contaminant removed, but mediator-based control ($F[1, 24] = 9.523,\ p = 0.009$) shows a significant difference across the scenarios, suggesting that mediator-based control scales better with workload. Importantly, mediators outperform leaders and predators, which is not surprising since we designed the scenarios to require swarm control compatible with mediator-based influence. Moreover, because the initial condition of high workload scenario includes more oil contaminant than the initial amount of oil contaminant in low workload scenario, removed contaminant score for the mediator method was increased under high workload conditions.

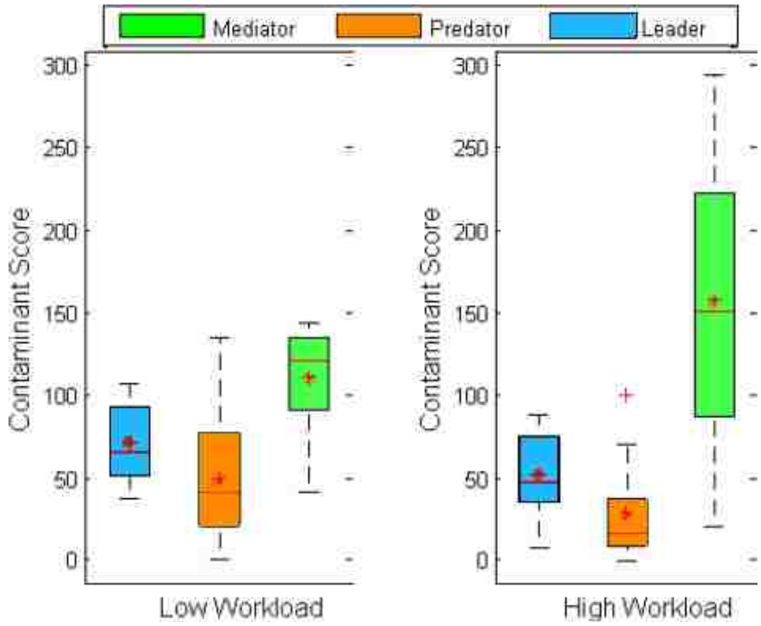
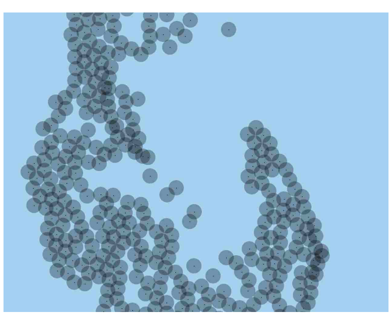
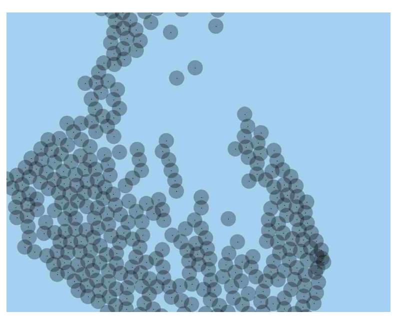


Figure 3.9: Removed contaminant scores for each scenario.

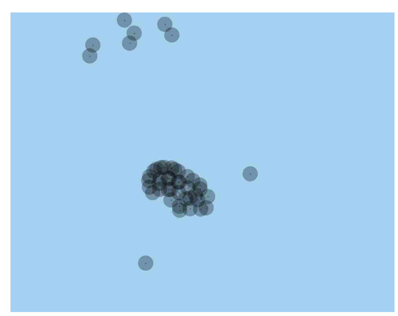
The amount of area that is contaminated after three minutes shows no significant difference across the scenarios, but there are significant differences among the informed agents ($F[2, 36] = 46.235,\ p < 0.001$). Fig. 3.10 illustrates that mediators tend to gather the oil contaminant into one place and prevent the oil from expanding over the ocean surface.



(a) Leader



(b) Predator



(c) Mediator

Figure 3.10: Contaminated area in the map of each informed agent.

These two measures indicate that the mediator-based control performs better than either leader- or predator-based control for this task.

3.8 Conclusion and Future Work

We introduced a mediator-based control model for human-swarm interaction and demonstrated that this model can be used to transform a swarm into a variety of shapes. Because mediator-based swarm control allows a swarm to maintain a torus formation while it is moving, the swarm retains the advantages of torus behavior, in contrast to previous work on leader- and predator-based control. We also investigated how the mediator-based control is better in managing swarms and performing decontamination task. Future work will study whether mediated swarms can be robustly applied to real robots. Future work will also examine how robustly the mediator model can handle a variety of shapes.

Acknowledgment

We appreciate the Science of Autonomy program of the Office of Naval Research for funding this work. The opinions of this paper do not necessarily reflect the funding agency.

Chapter 4

User Study Results

In Chapter 3, we designed the pilot study to measure the manageability and the performance of the mediated-based control. For better statistical analysis, we recruited 17 more participants from the campus of the Brigham Young University, 7 males and 10 females. For this user study, we were able to gather the data from total 30 participants, including previous 13 participants, 15 males, 15 females, ranging from 18–32 years old (average 24.2). This user study design and process are exactly the same as the pilot study.

4.1 Results and Discussion

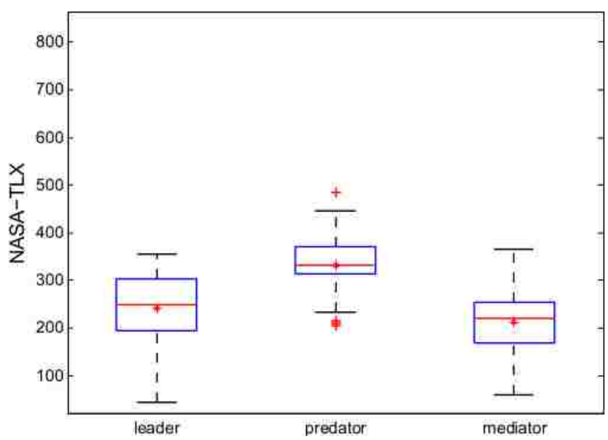
In this section, we compare the result from pilot study to the result of user study. As we did in the previous chapter, we address the following two questions. First, does mediator-control improve the manageability of a robot swarm? Second, does mediator-control increase the performance of decontamination task? Data was analyzed using a repeated measures ANOVA.

4.1.1 Manageability

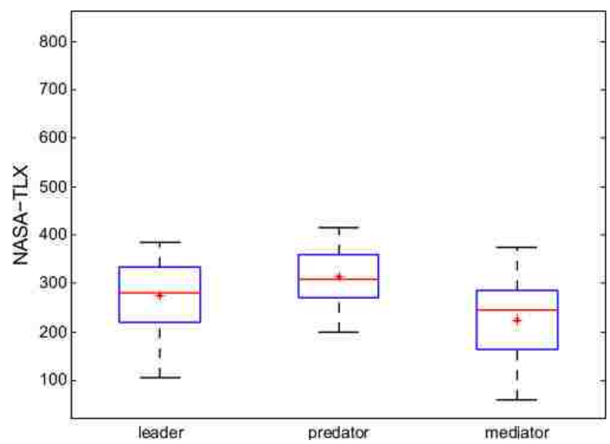
The result of the manageability measure for the user study is very similar to the result of the pilot study. Table 4.1 shows that the score for mediators is a little higher than others, but the ANOVA for the secondary task revealed that there is no significant difference across the scenarios ($F[1,58] = 1.784,\ p = 0.264$) and among the three informed agents ($F[2,87] = 3.16,\ p = 0.06$). We observed that the secondary task score from the user study dropped a little bit as compared with the score from the pilot study. The score for mediator

($\downarrow 0.025$) decreased less than the scores for leader ($\downarrow 0.053$) and predator($\downarrow 0.132$). This result does not show a significant difference, and the study may require more data for better analysis.

For the score of NASA-TLX across the scenarios for predators ($F[1, 58] = 4.819,\ p = 0.036$) and leaders ($F[1, 58] = 7.481,\ p = 0.01$), there are significant differences. However, the mediator showed no significant difference ($F[1, 58] = 0.251,\ p = 0.62$) across the scenarios. Figure 4.1 illustrates that workload increases when using leaders and may actually decrease using predators, but stays relatively flat for mediators. It also shows that the mediator's NASA-TLX score is the lowest, and it is significantly different among the informed agents ($F[2, 87] = 32.275,\ p < 0.001$).



(a) Low Workload



(b) High Workload

Figure 4.1: NASA-TLX scores

Table 4.1 shows that the leader has the highest sustainability. On the other hand, the mediator's sustainability is similar to the predator's because when the shape gets bigger, uninformed individual has more chances to interact each other and less chance to interact with mediators. As we discussed in Chapter 3, this result is not what we expected based on the result from [14]. However, according to some comments (Appendix B.3.2) from participants, they feel more comfortable with a leader than with other informed agents even though they had scored higher using the mediator. This implies that high sustainability enables a human to manage a swarm easily, but is less important for problems where a swarm must be shaped than for a swarm that must flock to different locations.

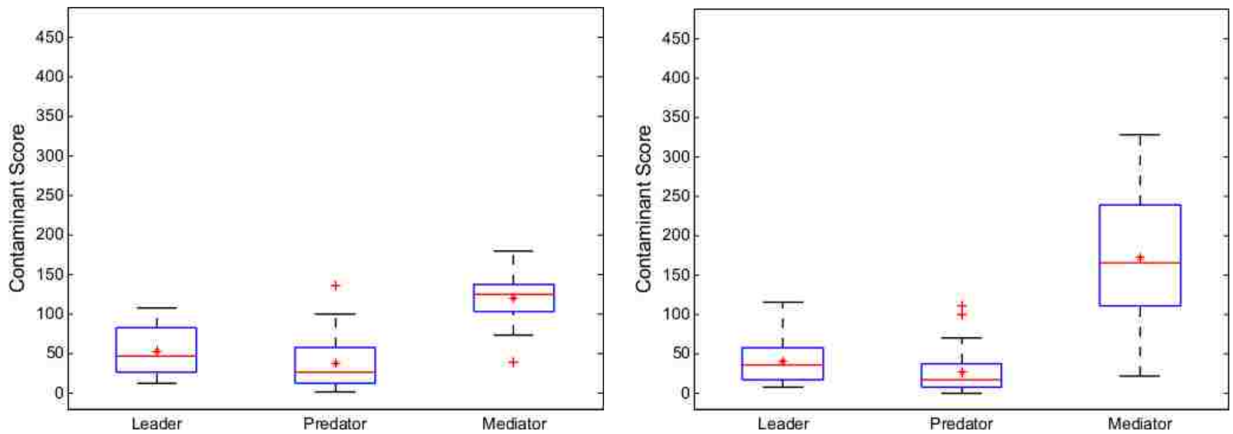
		Leader	*Predator*	*Mediator*
Pilot Study	Secondary task score	1.71	1.69	1.75
	Sustainability	176.2	17.92	17.71
	Travel Dist.(unit)	889.54	1054.97	249.0
User Study	Secondary task score	1.657	1.558	1.725
	Sustainability	178.609	19.209	14.824
	Travel Dist.(unit)	3429.524	4403.549	1226.012

Table 4.1: Qualitative results from pilot study and user study.

However, the total distance traveled by the mediators' is much lower than the distances of other informed agents as shown in Table 4.1. As illustrated in Figure 3.8, it is easy to see that mediators need to move less to manage the swarm than the other two informed agents. This impacts the strategies used to control the uninformed agents. Because leaders facilitate sustainable influence, participants tended to gather all agents in the swarm near the contaminants and then guide this cluster from contaminant to contaminant. For predators, participants tended to turn the swarm into several groups of flocks and tori, which they then "pushed" to different contaminant areas; the predators were then moved around the map to guide the separate groups. Because of this, predators tend to travel a lot. Participants tended to place mediators near the boundaries of the spill and then move the mediators toward the source of the spill as contaminants were removed, resulting in little travel distance.

4.1.2 Performance

Leader-based control ($F[1, 58] = 10.113,\ p = 0.003$), predator-based control ($F[1, 58] = 4.333,\ p = 0.046$), and mediator-based control ($F[1, 58] = 19.036,\ p < 0.001$) show a significant difference in the amount of contaminant removed across the scenarios. Because the high workload scenario includes much more oil contaminants and ocean currents, all informed agents should perform different than the low workload scenario. In the pilot study,



(a) Low Workload

(b) High Workload

Figure 4.2: Removed contaminant scores for each scenario.

mediator-based control did not reveal significant difference in the amount of contaminant removed across scenarios. Leader- and predator-based control both show a significant decrease of the score, but mediator-based control shows a significant increase of the score. As shown in Figure 4.2, mediator-based control appears to scale better with workload. Importantly, mediators outperform leaders and predators, which is not surprising since we designed the scenarios to require swarm control compatible with mediator-based influence. Moreover, because there were many more initial contaminants in the high workload scenario than the low workload scenario, it is not surprising that the contaminant score for the mediator method was significantly higher for the high workload condition.

The amount of area that is contaminated after three minutes shows no significant difference across the scenarios, but there are significant differences among the informed agents ($F[2, 87] = 46.235,\ p < 0.001$). As we described in Chapter 3, mediators tend to gather the oil contaminants into one place and prevent the oil from expanding over the ocean surface. This also explains why the mediator-based control performance improves on the high workload scenarios. The effective strategy for using mediators, confining and gathering the oil contaminants, performs better when there are more oil contaminants.

4.2 Chapter Summary

Through this user study, we were able to gather more data, performed better statistical analysis on the experiments. The results in this chapter are very similar to the results in 3. The measurements of both manageability and performance indicate that the mediator-based control performs better than either leader- or predator-based control for this task.

Chapter 5

Physical Demonstration

In this chapter, we present work that gives evidence that the simulation-based results in the previous chapters apply to real robots. We used a physical robot called Turtlebot (Figure 5.1).

In the Human Centered Machine Intelligence (HCMI) lab, we have two Turtlebots that run with the Robot Operating System (ROS) [28]. ROS is a useful tool for creating robot swarm algorithms because ROS includes built-in algorithms that we can use for sensors, building maps, and control. There are enough sources of documentation on the web so that we can build the system with our swarm model. To apply our swarm algorithm to real robots, we need to overcome two limitations: enabling robots to use real sensors to estimate the distances and direction that they need to swarm, and finding a way to have confidence in the swarming results given that we only have two physical robots.

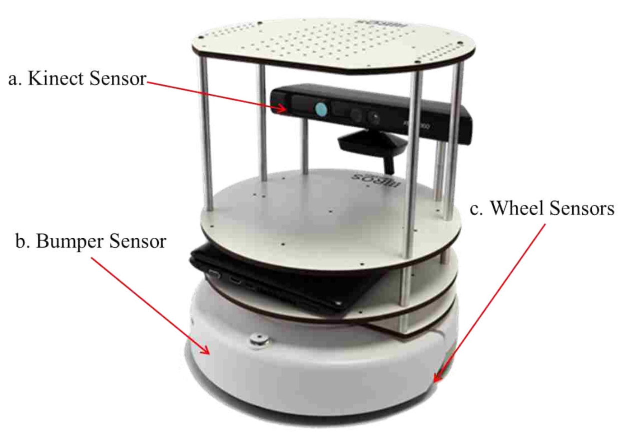
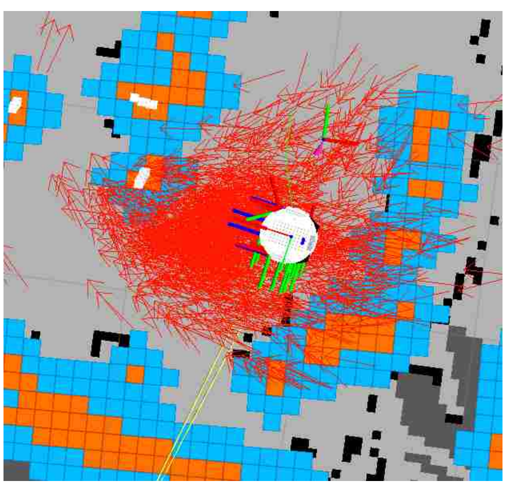


Figure 5.1: Turtlebot. a gives information about color, depth, and acceleration. b gives distance information, and c gives information about speed and direction.

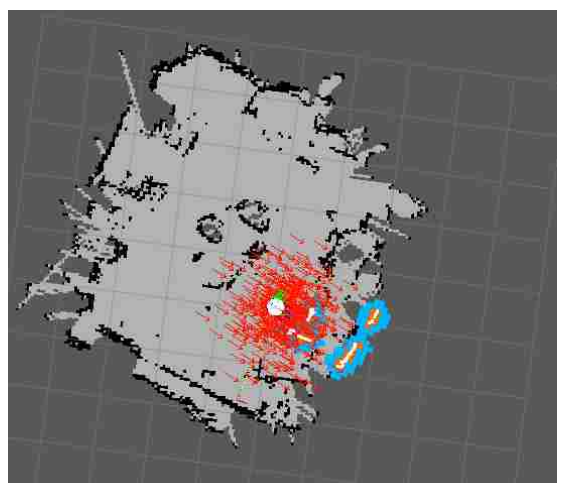
5.1 Feasibility of Real Sensors

Results in this thesis and chapter ignore dynamic environments where the locations of walls and obstacles can change over time. Instead, we built a static environment. This means that the robots have complete knowledge of the entire environment albeit one that may be noisy. The ROS includes a particle filter mapping algorithm called GMapping. We used the GMapping algorithm to build the environment so that we can apply the swarm algorithm into the robots without handling an uncertain environment.

The GMapping algorithm performs simultaneous localization and mapping for robots using a Kinect sensor. Figure 5.2 shows how we used kinect sensor to draw the map of the HCMI lab in the Talmage building at BYU. While building the environment map, enabling the robot to the sensor generate a point cloud to localize the robot's initial position on the map, enabling the robot to track its current position as it moves in the world.



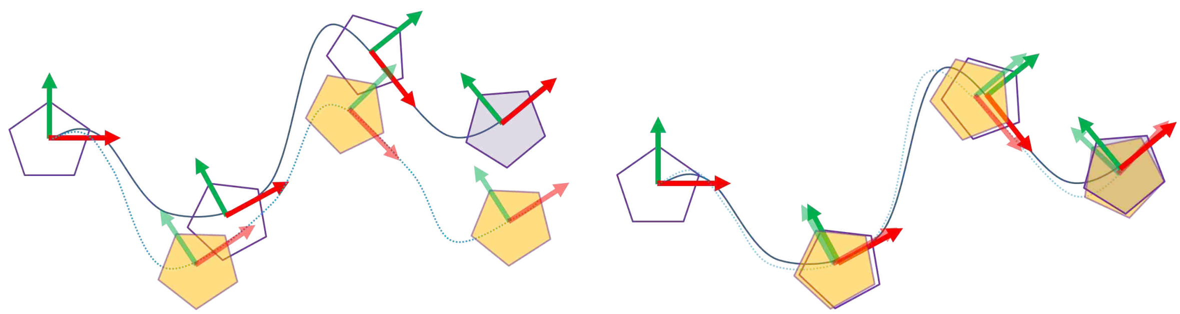
(a) Point Cloud Localization.



(b) Building maps through the GMapping.

Figure 5.2: Gmapping and localization.

After the robot is initially positioned on the map, the robot used its wheel sensors to localize its position on the static environment while it is moving. We also used the Adaptive Monte Carlo localization (AMCL) approach to estimate the position of the robot to improve



(a) Odometry. (b) Odometry with probabilistic localization system.

Figure 5.3: Robot position estimation accuracy.

the wheel sensor odometry. As shown in Figure 5.3, if the robot only used its wheel sensor to localize, there is a big gap in between the actual position of the robot and the estimating position. However, if the robot uses both wheel sensor and AMCL approach, it highly improves the robot localization.

Brian Pendleton verified the feasibility of the robot sensors in his master thesis by using them to avoid obstacles and escort a human operator in a simulated force protection scenario [27]. He also mimicked Couzin's swarm model by using the information from the robot sensors. This supports that we can also use the information of the robot's position and direction from the sensor in order to implement the physical mediator-based control model.

Mediator-based control model requires 180° of viewing angle. However, as shown in Table 5.1, the Turtlebot's horizontal field of view is only 57.0°. This problem can be resolved by generating the sensor information through the simulated robots. Pendleton examined the robot localization error by comparing the estimated robot position by the sensors to the observed position by cameras in the BYU MAGICC lab's motion caption room [27]. Setting the robot configuration with the localization error allows us to reveal approximate results in the robot simulation. Hence, we configured the simulated robots with the required parameters including Pendleton's localization error, and we broadcast the simulated sensor

Description	Value
Size	13.3 in (0.34 m)
Maximum speed	0.5 m/s (1.48 $unit/s$)
Maximum turning rate	1.57 rad/s ($90°/s$)
Viewing angle	43.0° vertical by 57.0° horizontal field of view
Maximum sensor range	$4.0 - 5.0$ m

Table 5.1: Physical parameters of TurtleBot.

information to the real robot to respond and move. Thus the real robot moved in the real world, but using a simulated sensor based on accurate sensor error ranges.

5.2 Robot Simulation and Physical Robot

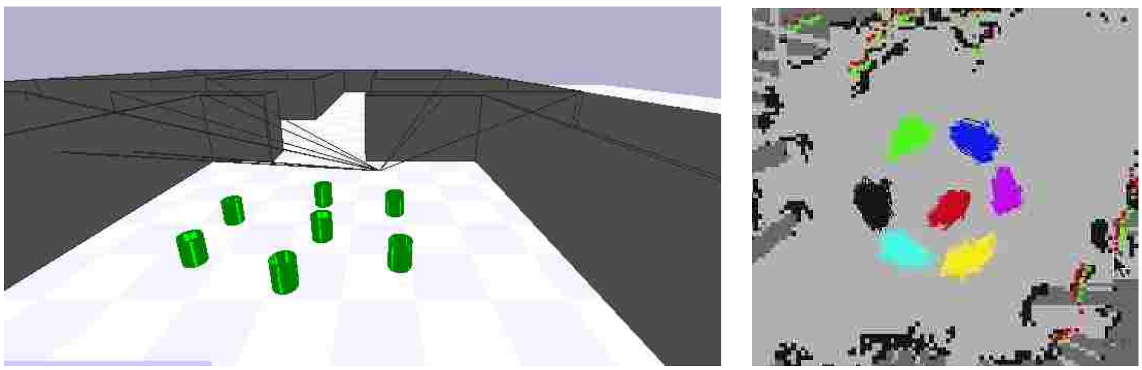
The second limitation is that we have only two robots. In order to build a full physical model of a swarm, we need to have about 50 to 100 robots. However, it is too expensive to buy that many robots. Thus, we built some simulated robots instead of having more robots, but these simulated robots used the same control algorithms and sensors as usable by the physical robot [27]. Thus, we perform two stages. First, we show that any control signals used in the simulation produce acceptable robot behavior on the physical robot. Second, we build a set of simulated robots that use these same controllers but that demonstrate swarming behavior. In the interest of simplicity, we only demonstrate the S-agents.

Parameter	Description	Value
s	Linear velocity	0.35 m/s
ω	Turning rate	$40°/s$
θ	Viewing angle	180.0°
R^{rep}	Range of Repulsion	0.35 m
R^{ori}	Range of Orientation	0.35 m
R^{att}	Range of Attraction	5.0 m
R^{pred}	Range of Mediation	1.0 m

Table 5.2: Parameters of Simulated TurtleBot.

5.2.1 ROS Simulator and Physical Robot

We used the ROS Stage simulator with *rviz*[1] tool. The Stage simulator is simple and easy to manipulate, allowing us to use a good model of the Turtlebot and to create useful environments. The *rviz* tool provides a visualization of a robot's sensors.



(a) Perspective view in Stage simulator. (b) Direction view in *rviz* tool.

Figure 5.4: Stage simulator with Robot Operating System. Figure (*b*) illustrates the point cloud around the robot model. This tells us the direction and the position of each robot.

Through running simulated robots with the setting described in Table 5.2, we were able to form a torus formation rotating around the mediator robot (Figure 5.4). Given that we were able to form a torus around a mediator, we ran a simulation in which we moved the mediator robot to test whether the torus would maintain its shape as it moved a long with the mediator. We were able to successfully control the mediator-robot to move the swarm while maintaining the torus behavior as shown in Figure 5.5.

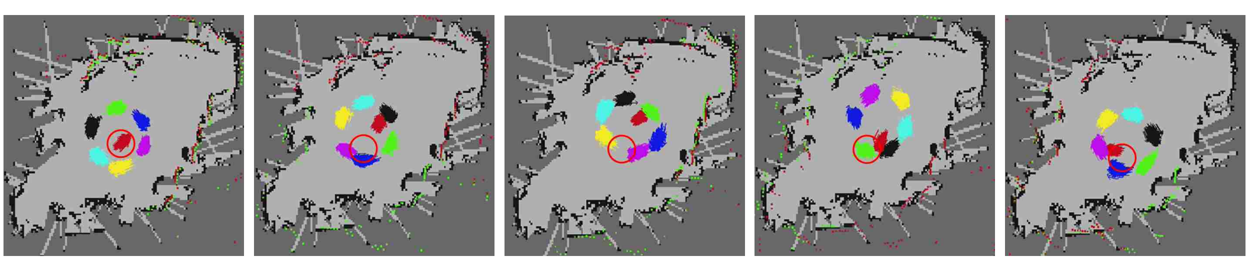
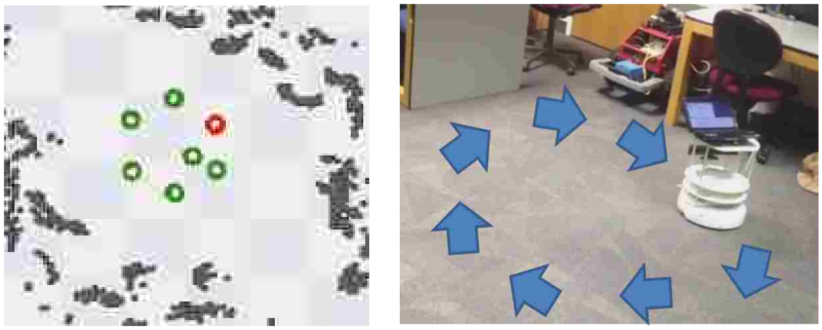


Figure 5.5: Illustration of Mediator-based control through *rviz* visualization tool. The red circle describes the initial position of the mediator. Left $\longrightarrow$ Right in sequence.

[1] 3D visualization tool for ROS: *www.ros.org/wiki/rviz*



(a) Stage simulation. (b) Physical robot.

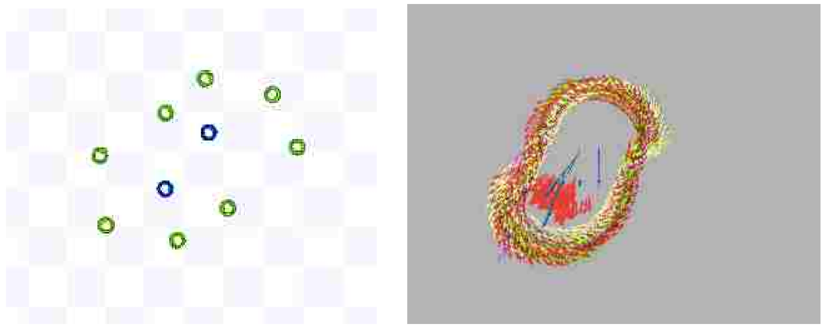
Figure 5.6: Stage simulator with a real robot.

After the simulation, we created a node[2] for the physical robot in ROS system to communicate with Stage simulator. This allows us to have a physical robot broadcast its sensor information to other agents, and receive information from the sensors of the simulated robots. Figure 5.6 shows the physical robot interacting with the simulated robots. The red colored circle represents the real robot on the right. We observed that the physical robot was able to form a torus behavior around the simulated-mediator model.

5.2.2 Shaping Simulated Swarm Robots

Because we verified that the robot sensor information from simulated robots can produce the swarm behavior with the physical robots, we attempted to form a perimeter shape of a swarm around more than one mediator. We placed two simulated mediator-robots in the center of 8 simulated robots, and moved one mediator slowly to form a bar shape. Because of the outdated hardware and unstable network connection, each simulated robot sometimes lost their connections and responded to each other slowly, and this caused lots of noise. Nevertheless, we were able to successively create a reasonable bar shape as shown in Figure 5.7 and validate that the robots with sensors can create the perimeter shapes around the mediator-robots.

[2] In ROS, all models such as sensors, robot, map, etc. are denoted by graph nodes. Each nodes is connected each other if they can broadcast/receive information.



(a) Top view. (b) Direction view.

Figure 5.7: Simulated mediators with nominal agents create a bar shape.

5.3 Chapter Summary

In this chaper, we verified that the simulated robots with the information from sensors can perform a torus behavior around the mediator, and the mediator-control can influence the swarm to move. Also, broadcasting the sensor information to the physical robot, we were able to observe that the simulation produced acceptable behavior on the physical robot while interacting with simulated robots. To perform a mediated swarm control without simulated sensor, the robot requires the sensor that covers 180°.

Chapter 6

Conclusions and Future Work

This thesis presents a new method of swarm control that improves the manageability and performance of a set of bio-inspired robots capable of exhibiting interesting and useful shaped torus structures. More specifically, with respect to our thesis statement (Section 1.1) we validated the following four hypotheses. First, there are suitable ranges of parameters for swarms in order to maintain the stability of a torus formation while interacting with humans. Second, the influence of a swarm by mediator agents increases the manageability of a swarm compared to what can be achieved by predators and leaders. Third, swarm-shaping through mediators is effective for performing a decontamination task that was designed to require a shaped torus-like group of robots. Fourth, swarm algorithm and the mediator agents can be applied to real robots and do meaningful tasks in real world.

Chapter 2 discussed three models based on Couzin's model [5] and analyzed the sensitivity and robustness. We included Daniel Brown's proof of the maximum speed of the torus, and provided evidence of this result with simulation. This results of the simulation found that the mediated swarms can be robustly applied in the noisy conditions which exist with real robots and provided evidence to support the first hypothesis. This work was successful because we demonstrated (1) there are a wide range of parameters for both nominal and mediator agents that allow a mediator to stay in the middle of a stable torus, and (2) the torus stays stable if the mediator agent slowly moves.

Chapter 3 includes extended model descriptions from Chapter 2, and discussed the user study with its results. The pilot study focused on an interesting application of using shaped perimeters to perform an oil decontamination task. Through evaluating manageability and performance of mediator agents with a swarm, we demonstrated that shaping a swarm by coordinated mediation is more effective than previous models (a leader or a predator) removing oil contaminants.

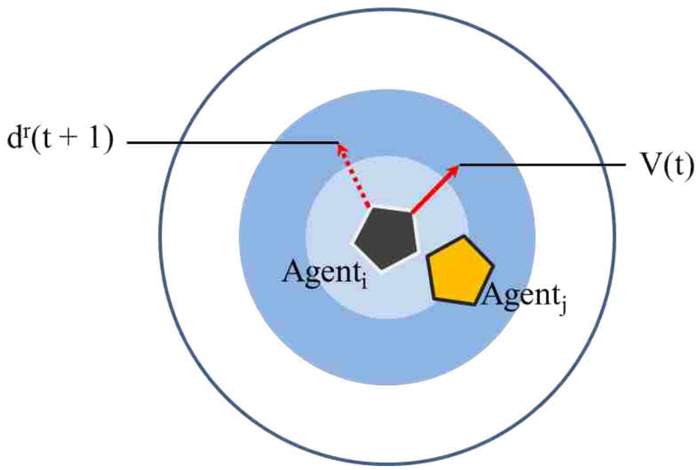
Chapter 4 discussed the result a more complete user study. The user study was based on the pilot study from chapter 3, and yielded similar results but with better statistical validity. The final result of the user study also supports our hypothesis: mediator-control method improve the manageability of a robot swarm, and mediator-control method increase the performance of decontamination task.

Chapter 5 addressed the physical embodiment with the swarm algorithm. We addressed two problems: using physical sensors to estimate robot positions and orientations, and providing evidence that the algorithms could be applied on real robots even though we had only two physical robots. We demonstrated physical controllers on the two real robots, and then used these same controllers in ROS-based simulations. We demonstrated that the robots perform a torus behavior around a physical-mediator model. Through this process, we made the initial step of applying the swarm algorithm in the real world.

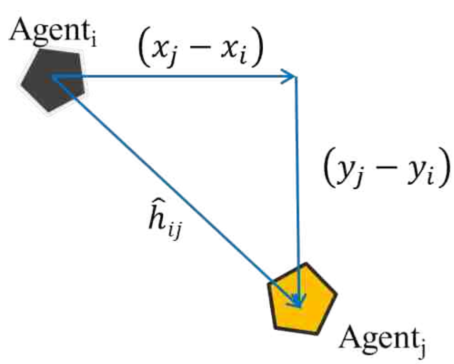
Future work should examine how robustly the mediator model can handle a variety of shapes. Also, because we just hit the surface of applying the swarm algorithm in the real world, work should take another step to demonstrate that the physical-mediator models interact with multiple physical swarm robots to transform the swarm formation into a variety of shapes. Finally, analysis should be performed that uses graph theory to explain why topologies produced by less connected agents, like the s-agent discussed in the thesis, produce agents that afford sustainable influence and robust torus shapes.

Appendix A

Mathematical Agent Model



(a) Desired direction d in zone of repulsion. v = current direction vector.



(b) Direction vector in zone of attraction.

Figure A.1: Direction d calculation in zone of attraction

When an agent perceives its neighbors' positions, which means that its neighbors are not in the blind spot, it calculates the desired direction vector using Equations (A.1)–(A.3), which lead it to the next movement. Equation (A.1) is for when an agent i sees its neighbor agents j in the zone of repulsion.

$$d_i^{rep}(t+1) = -\sum_{i \neq j}^{n} \frac{\hat{h}_{ij}(t)}{\|\hat{h}_{ij}(t)\|} \tag{A.1}$$

where t = time, $\hat{h}_{ij}(t)$ = vector of an agent i towards the neighbor agent j at time t, d_i = desired direction of an agent i, rep = repulsion, n = the number of agents. Figure A.1(a) illustrates that the agent's current direction will be rotated toward the new desired direction.

When the agents are in the zone of attraction, they use Equation (A.2).

$$d_i^{att}(t+1) = \sum_{i \neq j}^{n} \frac{\hat{h}_{ij}(t)}{\|\hat{h}_{ij}(t)\|} \tag{A.2}$$

where att = attraction. Figure A.1(b) represents the direction vector calculation when the agent is in the zone of attraction.

When the agents are in the zone of orientation, they attempt to find the neighbors direction and follow them by calculating Equation (A.3).

$$d_i^{ori}(t+1) = \sum_{j=1}^{n} \frac{\hat{v}_j(t)}{\|\hat{v}_j(t)\|} \tag{A.3}$$

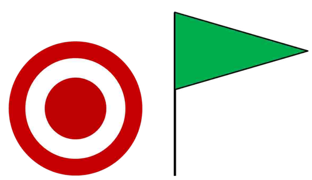
where ori = orientation, and $\hat{v}_j$ is neighbor j's direction vector. The desired direction in the orientation zone is obtained by adding all the neighbors' current normalized direction vectors. As we mentioned about the priority above, if the agents are in the zone of repulsion, they ignore other influences. If the agent has no neighbors in its zone of repulsion, it chooses the direction by $d_i(t+1) = d_i^{att}(t+1) + d_i^{ori}(t+1)$.

Appendix B

User Study Scenario, User Interface, Survey, etc.

B.1 User Interface

During the user study, participants saw the screen as Figure B.2 shown. One the top-left side, there are scores and elapsed time with red-colored font. The participants moved the mouse cursor B.1(b) and made an order by positioning the flag icon B.1(a).



(a) Cursor. (b) Flag.

Figure B.1: A Cursor and a flag.

The participants can control three different types of influencer, a leader, a predator, and a mediator. The leader B.3(a) can attract other agents so that human can lead them to the user expected direction. The predator, on the other hands, can repel the agents to change their directions B.3(b). The mediator is positioned in the center of the agents B.3(c) so that the agents can circling around the mediators to form a various perimeter-shape.

B.2 Scenario

Here is the scenario and instruction for the user study:

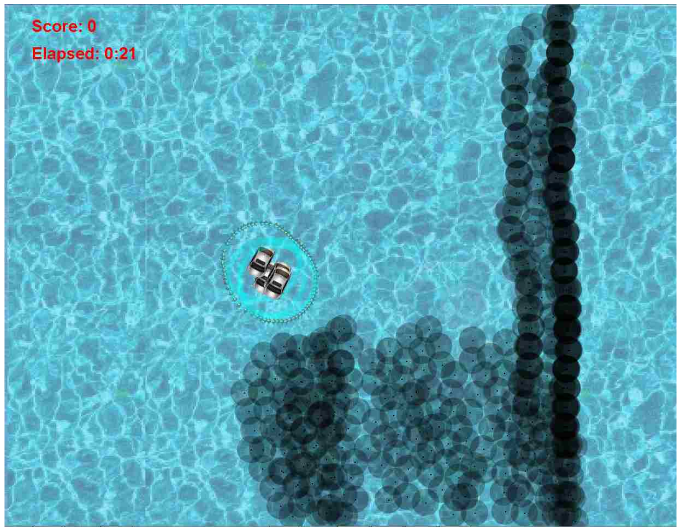
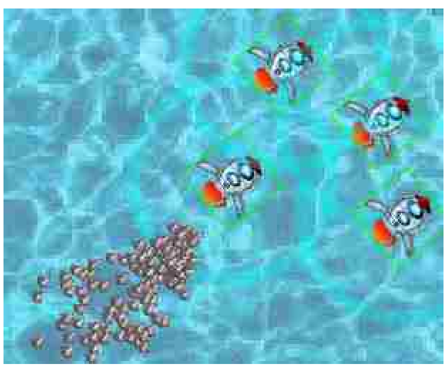
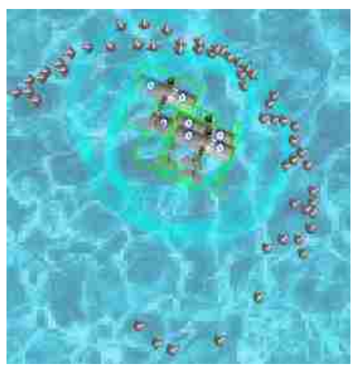


Figure B.2: User Interface.



(a) Leader.



(b) Predator.

(c) Mediator.

Figure B.3: Three types of influencers.

Now, you are ready for the real application! In the middle of pacific ocean near the island of Oahu, an oil tanker contains 30,000 gallons of oil hit a reef. An oil spill causes an environmental disaster, destroying beaches,coating birds and oysters with oil, and driving away tourists with its stench. Your job is to prevent oil from expanding over the ocean surface and to clean up as much of the oil as you can. The small robots absorb and repel the oil, so you can use these robots to accomplish your job. If the small robots are near enough to the oil for long enough, the oil is absorbed.

Also, if you can wrap around the oil with small robots, the oil will be removed. For this trial, you will use four leaders (predators, or mediators) to control the small robots. Contain and absorb as much oil as you can in the next three minutes.
To choose a single robot, click the left mouse button.To choose multiple robots, hold the SHIFT button and left click on the robots. To select all robots, press the CTRL key. To move selected robots click the right mouse button on the destination. You can increase the speed of the selected robot by pressing the 'w' key. You can decrease the speed by pressing the 's' key.
You will also hear the two different sounds during the task. During your mission, if you hear the CORRECT SOUND, press SPACE BAR as soon as possible. If you hear the WRONG SOUND, you don't need to do anything. Before moving to the next, click the WRONG SOUND button on the bottom left, and click the CORRECT SOUND button. Good luck!
When you are ready, press "Next" to start the mission.

B.3 Survey Questions

B.3.1 Pre-survey and Results

Please follow the directions below and answer the questions. If you are not comfortable answering a question, you are not required to answer it, and may skip the question.

1. Sex
   (a) Male
   (b) Female
2. Age
3. Do you have normal vision or corrected-to-normal vision?
   (a) Normal
   (b) Corrected-to-normal

4. Do you have color blindness?
   (a) Yes
   (b) No
5. What is your level of experience working or playing with robots?
   (a) Extremely experienced
   (b) Very experienced
   (c) Moderately experienced
   (d) Slightly experienced
   (e) Not at all experienced
6. Experience playing video games
   (a) Extremely experienced
   (b) Very experienced
   (c) Moderately experienced
   (d) Slightly experienced
   (e) Not at all experienced

B.3.2 Post-survey

Please follow the directions below and answer the questions. If you are not comfortable answering a question, you are not required to answer it, and may skip the question. Please answer these questions about your overall experience during this experiment.

1. Which type of influence make it easier to perform the tasks?
   (a) Leader
   (b) Predator

(c) Mediator

2. Which type of influence is more efficient to perform the tasks?

   (a) Leader

   (b) Predator

   (c) Mediator

3. Rank the following. (The easy of uses) - smaller number is the easier.

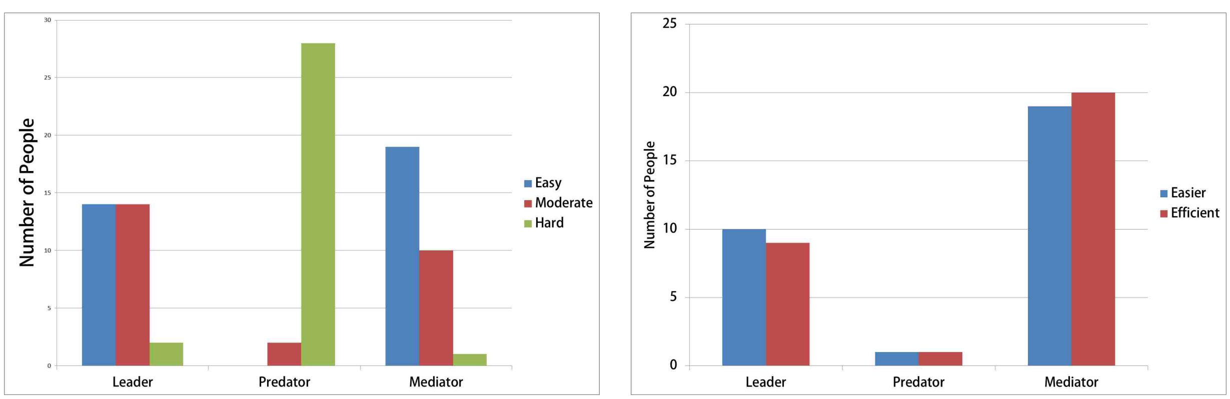
   (a) Leader - select 1,2, or 3

   (b) Predator - select 1,2, or 3

   (c) Mediator - select 1,2, or 3

4. Any other comments?

Post-survey results and comments



(a) Difficulty. (b) Efficiency vs. The easy of use.

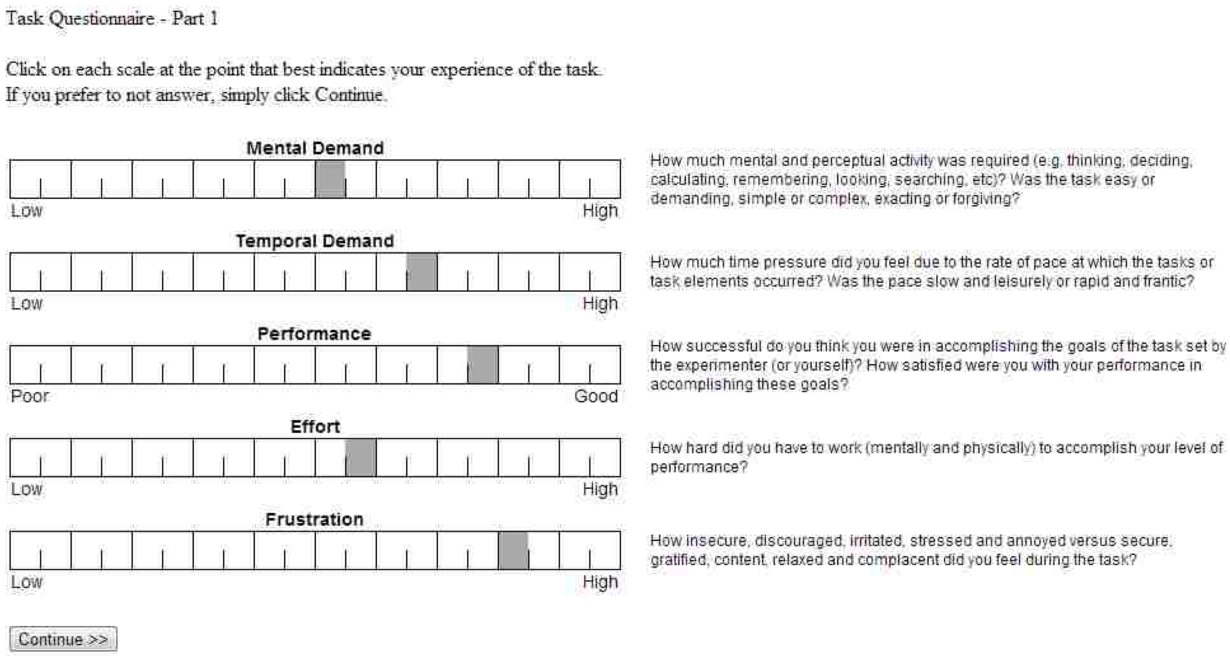
Figure B.4: Post-survey results.

1. fun game.

2. It was sometimes hard to tell how effective I was. I think I may have scored higher using the Mediator, but I felt more effective with the Leader.

3. Thank you
4. The huge portion of oil spots makes me feel not accomplished even after removing much of it.
5. Predator is extremely difficult and frustrating to use; resultant behavior is often different from what is expected, both with regards to directly controlled agents and those being herded. Leader types are very simple to use with adequate levels of efficiency; they are essentially a "point and shoot" type design. That notwithstanding, efficient use of leader types requires dividing them up and dispatching them to different locations, which exhibits some degree of temporal cognitive demand. Mediators were surprisingly simple to use, and rather effective as well, although the dynamics of how the larger herd shape followed the individual mediator actions took some getting used to.
6. Neato burrito
7. Awesome! Save the Dolphins!

B.3.3 NASA-TLX



Task Questionnaire - Part 1

Click on each scale at the point that best indicates your experience of the task.
If you prefer to not answer, simply click Continue.

Mental Demand

Low — High

How much mental and perceptual activity was required (e.g. thinking, deciding, calculating, remembering, looking, searching, etc)? Was the task easy or demanding, simple or complex, exacting or forgiving?

Temporal Demand

Low — High

How much time pressure did you feel due to the rate of pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic?

Performance

Poor — Good

How successful do you think you were in accomplishing the goals of the task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals?

Effort

Low — High

How hard did you have to work (mentally and physically) to accomplish your level of performance?

Frustration

Low — High

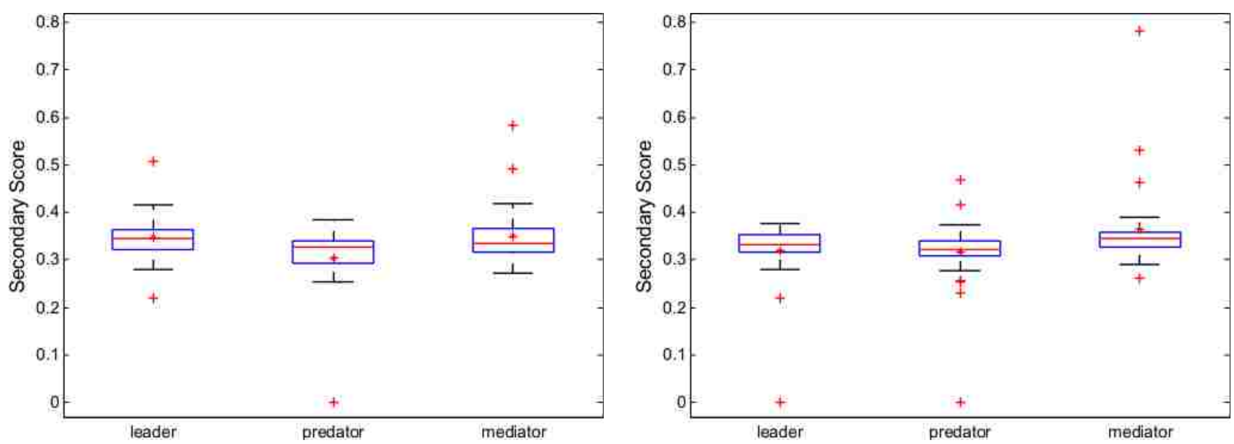
How insecure, discouraged, irritated, stressed and annoyed versus secure, gratified, content, relaxed and complacent did you feel during the task?

Continue >>

Figure B.5: NASA-TLX Survey.

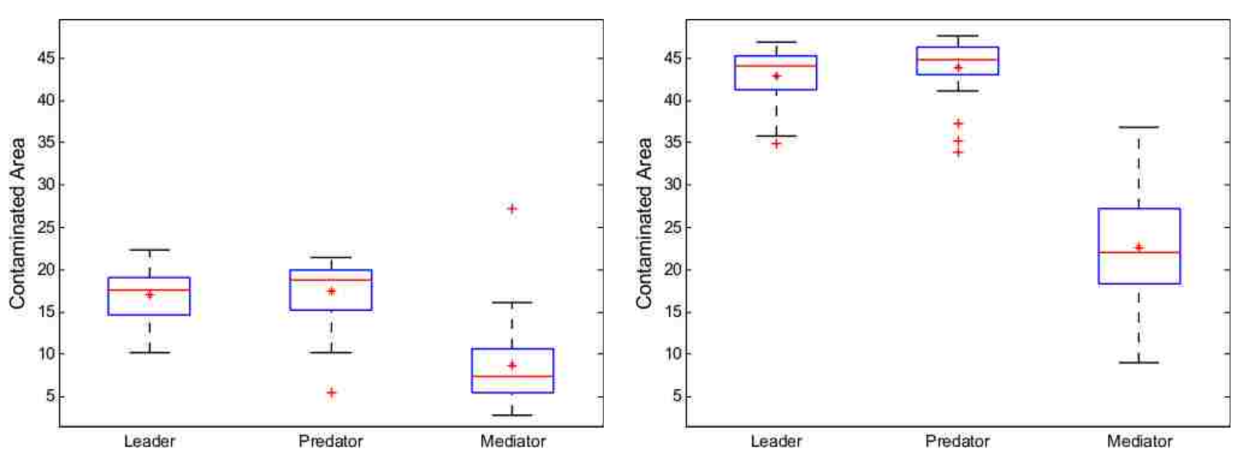
Appendix C

Graphs generated from User Study



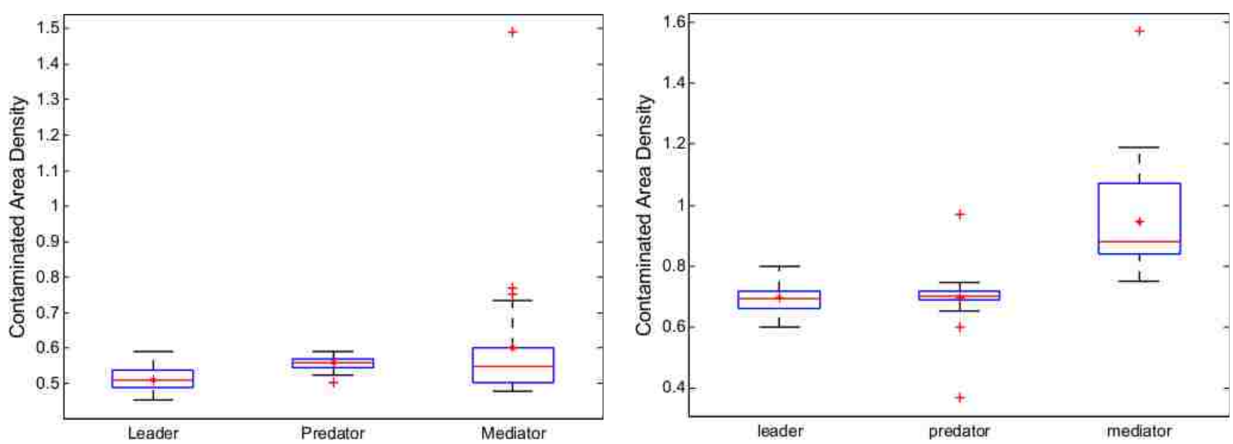
(a) Low Workload (b) High Workload

Figure C.1: Secondary task scores.



(a) Low Workload (b) High Workload

Figure C.2: Contaminated area for each scenario.



(a) Low Workload

(b) High Workload

Figure C.3: Contaminated area density for each scenario.

Appendix D

Repeated Measures ANOVA Data across the scenarios

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.016742	1	0.016742	7.480658	0.010526	4.182964
Error	0.064904	29	0.002238			

Table D.1: NASA-TLX score of leader-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.013625	1	0.013625	4.818704	0.036307	4.182964
Error	0.081999	29	0.002828			

Table D.2: NASA-TLX score of predator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.001082	1	0.001082	0.251101	0.620083	4.182964
Error	0.125002	29	0.00431			

Table D.3: NASA-TLX score of mediator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.011464	1	0.011464	3.626148	0.066842	4.182964
Error	0.091685	29	0.003162			

Table D.4: Secondary score of leader-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.002617	1	0.002617	0.763845	0.389308	4.182964
Error	0.099361	29	0.003426			

Table D.5: Secondary score of predator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.002796	1	0.002796	0.963223	0.334494	4.182964
Error	0.084169	29	0.002902			

Table D.6: Secondary score of mediator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.005855	1	0.005855	0.37868	0.54311	4.182964
Error	0.4484	29	0.015462			

Table D.7: Travel distance of leader-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.04657	1	0.04657	2.156158	0.152763	4.182964
Error	0.626361	29	0.021599			

Table D.8: Travel distance of predator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.019399	1	0.0019399	4.803624	0.036579	4.182964
Error	0.117117	29	0.004039			

Table D.9: Travel distance of mediator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.063006	1	0.063006	10.11312	0.003491	4.182964
Error	0.180674	29	0.00623			

Table D.10: Contaminant Score of leader-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.035187	1	0.035187	4.33263	0.046309	4.182964
Error	0.235502	29	0.008121			

Table D.11: Contaminant Score of predator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.192368	1	0.192368	19.03631	0.000148	4.182964
Error	0.293055	29	0.010105			

Table D.12: Contaminant Score of mediator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.000422	1	0.000422	0.288162	0.595496	4.182964
Error	0.042514	29	0.001466			

Table D.13: Contaminated Area of leader-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.000138	1	0.000138	0.084138	0.77383	4.182964
Error	0.047491	29	0.001638			

Table D.14: Contaminated Area of predator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.001043	1	0.001043	0.465219	0.500607	4.182964
Error	0.065002	29	0.002241			

Table D.15: Contaminated Area of mediator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.001373	1	0.001373	1.600536	0.215899	4.182964
Error	0.024875	29	0.000858			

Table D.16: Contaminated Area Density of leader-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.022515	1	0.022515	18.75254	0.000162	4.182964
Error	0.034819	29	0.001201			

Table D.17: Contaminated Area Density of predator-based control.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
low vs. high	0.035008	1	0.035008	13.86142	0.000844	4.182964
Error	0.073241	29	0.002526			

Table D.18: Contaminated Area Density of mediator-based control.

Appendix E

Repeated Measures ANOVA Data across the Informed Agents

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
Informed Agents	0.313941	2	0.156971	32.27511	3.79E-10	3.155932
Error	0.282084	58	0.004864			

Table E.1: NASA-TLX scores. Informed Agents: leader, predator, and mediator.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
Informed Agents	0.032677	2	0.016339	3.059391	0.054556	3.155932
Error	0.309747	58	0.00534			

Table E.2: Secondary scores. Informed Agents: leader, predator, and mediator.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
Informed Agents	4.663576	2	2.331788	113.2814	9.29E-21	3.155932
Error	1.193874	58	0.020584			

Table E.3: Contaminant scores. Informed Agents: leader, predator, and mediator.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
Informed Agents	0.763058	2	0.381529	149.6113	1.27E-23	3.155932
Error	0.147906	58	0.00255			

Table E.4: Contaminated area. Informed Agents: leader, predator, and mediator.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
Informed Agents	0.116096	2	0.058048	54.28549	5.16E-14	3.155932
Error	0.06202	58	0.001069			

Table E.5: Contaminated area density. Informed Agents: leader, predator, and mediator.

Source of Variation	*SS*	*df*	*MS*	*F*	*p − value*	*F crit*
Informed Agents	1.521751	2	0.760875	39.94658	1.24E-11	3.155932
Error	1.104745	58	0.019047			

Table E.6: Travel distance. Informed Agents: leader, predator, and mediator.

Appendix F

ROS Node connection in Stage Simulator

Figure F.1: ROS frame description about nodes of each robot and its sensors.

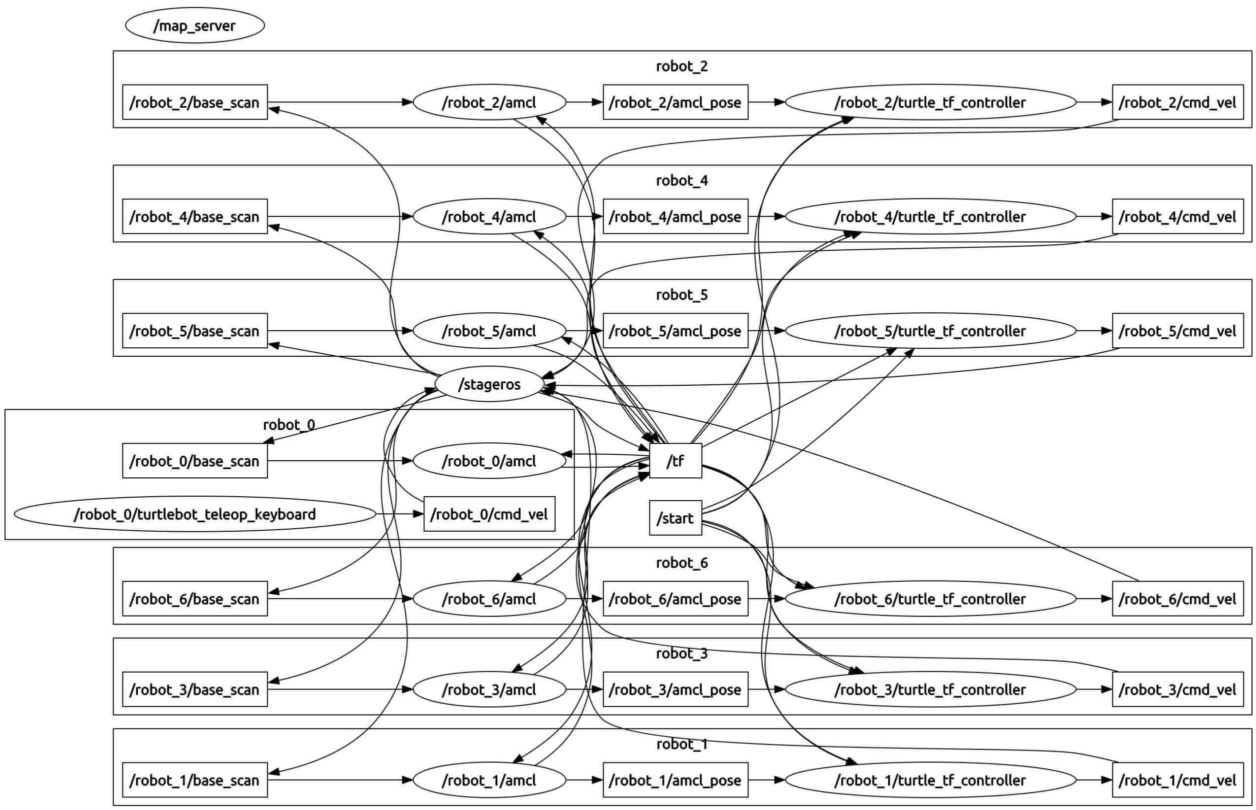


Figure F.2: Entire node graph in ROS. $/tf$ node includes the physical model descriptions of robots. */cmd_vel* node includes the information of robot's linear and angular velocity. */base_scan* node has sensor information. */amcl* node receives the information from the */base_scan* node and estimates the position. */amcl_pose* receives the position information from the */amcl* node and broadcast to the robot. */turtlebot_teleop_keyboard* allows an operator to control a mediator-robot.

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