Kinesis-based Swarming Scheme for Mobile Sensors

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ABSTRACT

We are examining a kinesis swarming scheme that is based on the simple sensing of a pill bug. Here we present a mobile sensor with limited processing power and simple sensors to swarm a gradient based phenomena. We are seeking to define rules and perform tasks through the combination of many simple, concurrently reacting behaviors. We are researching ways to use behaviors as the framework for small, actuation sensing devices to perform swarming without the need for global environmental data. Thus, we are conserving the resource power needed for global updating that can be used for other activities. An advantage of our approach is the ability to self-adapt to changing environments by providing movement and swarming behavior based on simple, rudimentary kinesis rules.

1. INTRODUCTION

We present a kinesis swarming scheme based on the behaviors of the pill bug [1]. The concept of kinesis is elaborated in section 3 of this paper. Pill bugs have an innate capability to quickly find humid areas where they are most conformable. They accomplish this in a non-intrusive way, using very simple behavior rules. This paper explores this concept in swarming for resource constrained area monitoring using mobile sensors.

Our inspiration comes from the behaviors associated with the Pill bug. These simple crustaceans perform movement related behaviors as noted in many lab studies [1]. In section 2, we present related work for the problem addressed in this paper. We provide an overview of our approach in section 3. In section 4, we explore the autonomous behaviors that allow the mobile sensors to explore their environment. We conclude by showing our simulation results and introduce the effects of communication on the overall results when compared to non-communication devices. By comparison, we show that our bio-inspired swarming scheme presented here provides benefits when inter-communication is implemented. We discuss our future research goals, by building upon research presented in this paper.

2. CURRENT RELATED WORK

Different approaches have been introduced in the field of exploration, searching, and monitoring using a swarm of agents with sensing capabilities (mobile sensors). In situations where the terrain is known, it is common to use a tree based algorithm. In unknown environments, algorithms inspired by ant behaviors for real-time search have been studied [2, 3, 4].

While this related work has great properties, it is not applicable to the swarming problem we are investigating in this paper due to our resource constrained hardware. The pheromone approach introduces an intrusion, which we are trying to avoid in our scheme since it introduces more complexity and would change the sensing behaviour. The use of deterministic movements and infinite supply of information available at each decision point is impractical with our mobile sensors. The mobile sensors have limited computational abilities and memory constraints, not allowing for constant communication or storage of global path information. Movement is determined by the sensors that are mounted on simple, wheeled devices. These restrictions allow for resource conservation for target hardware.

3. KINESIS-BASED SCHEME

Kinesis is a movement which depends on the intensity of the stimulation. With orthokinesis, the stimulus produces a change in the animal's movement speed. In our scheme, the pill bug slows down when it finds a desired area. With klinokinesis, the animals turning rate is affected by the stimulus. Again, the pill bug's turning rate is increased when it finds a desired area. These two kinesis responses form the basis for our behavior rules.

We place these two rules in a behavior based priority driven architecture. This scheme is used as a basis to define a hierarchy of task accomplishing behaviors. Each behavior is defined using a simple rule-like structure, assigning each rule a priority. The mobile sensor evaluates each rule according to their priority. If a rule causes a true condition, the rule is performed and the evaluation begins again from the highest priority rule.

Our research begins by defining initial rules for how the mobile sensors will orientate and react to stimuli and changes in their environment. We have stepped back from the classical search planning approach that decomposes the task into teams of searching agents [5, 6] since it often suffers from the inherent sequence processing failures that occur when agents in those teams malfunction. We offer a more flexible approach by vertically decomposing the task in terms of achieving behaviors. This provides an architecture where behaviors are built by assembling a hierarchy of simple rules. We seek to clearly define the initial rules to begin our research and to provide a starting point for swarming behaviors. This provides a framework for implementation on constrained sensor equipment. Unlike traditional robots, mobile sensors have limited movement and computational abilities. This requires a simple, configurable rule based system that can be tailored for given sensor related swarming tasks.

4. SENSORY MOTOR RULES

4.1 Rule Set

Our architecture can be defined, as a collection of behaviors that are totally independent, have no inter-coupling to other behaviors, and they do not share state. This simplifies the development and allows for natural patterns to evolve that have not been explicitly defined. We define the following basic behavior rule set for our architecture. Each rule is defined in following sections 4.2 through 4.5.

- The highest priority behavior rule is obstacle avoidance.
  R1: *If detect an obstacle, then change direction*

- The second highest priority behavior rule is cooperation.
  R2: *If detect neighbor node, then communicate and check if another mobile sensor has found a gradient level. If received an event found message, then change direction toward event and communicate message to nearby neighbors.*

- The next priority behavior rule is target area search.
  R3: *If detect a target area, then perform kinesis movement (slowdown and turn more. Communicate event found message to nearby neighbors.*

- The lowest priority behavior rule is wander movement.
  R4: *If nothing to do, then move forward and turn randomly at given intervals*

4.2 Obstacle Avoidance Rules (R1)

We present behavior rules based on sensory input of the Pill bug. This basic behavior is a critical building block, since it has the highest priority. This type of behavior is commonly found in simple brained mammals [7], similar to the pill bug. Following our approach, we define the rules for the obstacle avoidance behavior.

Behavior is described as:

- The lowest level of behavior is obstacle avoidance.
  if detect an obstacle, then change direction

  Simple set of rules to realize the behavior:
  - if obstacle is in front: back up and turn left 30 degrees
  - if obstacle is on right: turn left 30 degrees
  - if obstacle is on left: turn right 30 degrees

The set of rules define the primitive behavior required for most mobile devices. We treat all obstacles, moving or fixed, as potential collisions and perform the defined rules. By determining the direction of the obstacle, the mobile sensors will perform the appropriate turn. We found that this behavior will continue, until the mobile sensor is clear of the obstacle allowing a lower priority behavior rule to be processed. Our findings show that this obstacle avoidance behavior is sufficient for our current research.

4.3 Cooperation Rules (R2)

Animals communicate in their native environments. For our swarming behavior, we are utilizing simple communication rules to notify nearby neighbors, within communication distance, of found gradient levels. Since the gradient covers a large area, this allows the other mobile sensors to converge on the area to find the highest gradient level.

If another mobile sensor has found a gradient level, the mobile sensor should move toward that location and communicate the message to all nearby neighbors. This allows for the message to multi-hop through the group. Our approach is similar to the ZebraNet [8] information passing scheme.

Since the mobile sensors are to be kept as simple as possible to reduce their cost and complexity, using a complex cooperation rule set to define their behavior is not an option in this case. Our approach provides a decentralized communication scheme that allows the mobile sensors to efficiently accomplish their task of swarming the event without requiring complex, centralized communication.

4.4 Kinesis-based Movement

Our movement rules are inspired from kinesis. The algorithm seeks to decompose the complex task of movement into layers of simple, biologically based behaviors. Our approach is based on the synergy between sensation and actuation of pill bugs. We are following an evolutionary path by observing simple agents in real, complex, and unpredictable environments. Our algorithm sets the orientation without respect to the direction of the stimulus. For the gradient search problem presented in this paper, the pill bug behavior provides the set of rules that closely resembles our objectives.

For the pill bug, its response can be to move toward or away from the stimulus depending on the predicated behavior. This movement may be in any direction or even random. The rate of movement (orthokinesis) and the frequency of turning (klinokinesis) depend on the intensity of the stimulation. In this case, the bug seeks out humid environments. They move more quickly within dry areas and they slow down their movements in high humidity areas. As they slow down, they increase their frequency of turning to remain in their preferred environment. This type of behavior allows for a very simple, yet effective technique for moving in the environment and required changes to movement in target areas.

Figure 1 shows the movement behaviors as found in our lab environment. As shown, the pill bugs are collecting in the high humidity area. Our research found that the bug would travel faster in the low humidity areas while turning less. We present our movement algorithm based on this behavior. It naturally provides two behaviors for movement within or outside a target area. The key properties of the algorithm follow our simple global rules:

- Global information is not known
- Behaviors are distributed rather than centralized
- Response to stimuli is reflexive

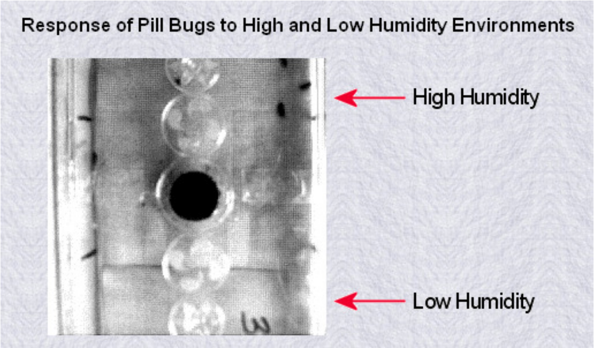

Fig. 1 Pill bug's behavioral lab study

4.5 Target Area Movement Rules (R3)

For target area movement, our rules are to move at a slower rate (referred here as target speed) and turn more frequently. Similar to the pill bug, our mobile sensors will seek out higher intensity areas. In our case, we seek out areas with a higher gradient signature.

- The next level of behavior is target area movement. *if detect a target area, then slow down and turn more*

  Simple set of rules to realize the behavior:
  - if gradient reading less than previous but within range: turn 240 degrees toward previous direction and reduce speed
  - if gradient reading greater than or equal to previous: maintain current direction and target speed

In our study, we found that each rule required further refinement. Based on the gradient signature, the rules should be emphasized by turning and slowing down more in higher gradient areas. We found that this allows for a more refined search and avoids missed sensor readings. This is a similar approach found in the pill bug study. Their movement slows to nearly stopping, once they find a humid area. Once the area becomes less humid, they begin their movement again. This is commonly found in their habitat of basements and crawl spaces. During the day, the sun affects the humidity in an area causing them to move.

4.6 Wander Movement Rules (R4)

For our wander movement, our rules are to move at a faster rate and turn less. This behavior allows the pill bug to leave unsuitable areas quickly. Similarly, our mobile sensors will seek out areas with a higher gradient signature.

- The last level of behavior is wander movement. *if nothing to do, then move forward and turn randomly at given intervals*

  Simple set of rules to realize the behavior:
  - move at a fast rate, turn randomly at given intervals

By moving at a faster rate, less time is spent on sensor readings. This allows our mobile sensors to cover more distance in each step while conserving energy. In our study, we set our turning rate at every ten intervals. This setting allowed the sensors to move quickly out of non-gradient areas while maintaining a high target area find rate.

5. PROOF OF CONCEPT SIMULATION

We used the Python Robotics simulator for our research [9]. We found that the simulated pill bugs closely follow the behavior of the real pill bug. As in nature, the pill bugs found the target area quickly and sufficiently. We say sufficiently, since this is a non-deterministic search approach. As shown in the simulations, the results (with random factors) find the source at different steps. We found that sometimes the simulated bugs (like the actual bugs) will wander in previous covered areas resulting in more steps to find the source. Several iterations reviewed more properties of the pill bug's movements. From this, we modified the rate of speed and turning distance. Similar Research has been done regarding swarming where individuals within the swarm send broadcasts that would affect the actions of the rest of the swarm. Such broadcasts can cause a swarm to converge on a location or create a convoy of agents in a swarm to get to an objective [10, 11].

For each simulation run, five mobile sensors are place in a field thirty-two units down and twenty-two units down (1 unit equals the length of a mobile sensor) as shown in figure 2.

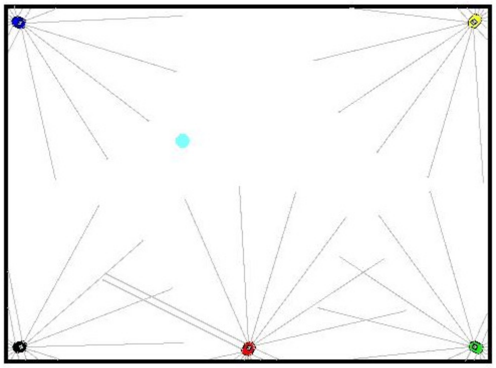

Figure 2: The starting positions for the mobile sensors.

In each simulation, the mobile sensors are searching for the source using the rules outlined in this paper. The source produces a plume, where the gradient degrades with distance. Each mobile sensor searches until it finds a gradient of ninety-five percent or higher. The simulation continues until all mobile sensors have reached the source as shown in figure 3.

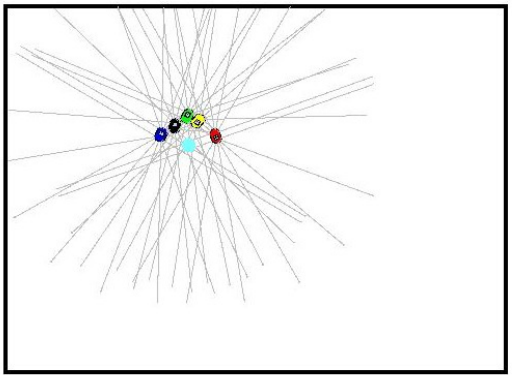

Figure 3: Ending positions of the mobile sensors.

The average number of steps required by each sensor to reach the source was recorded, as shown in figure 4 and table 1. The simulation was repeated thirty times with the cooperation rules disabled and another thirty times with them enabled.

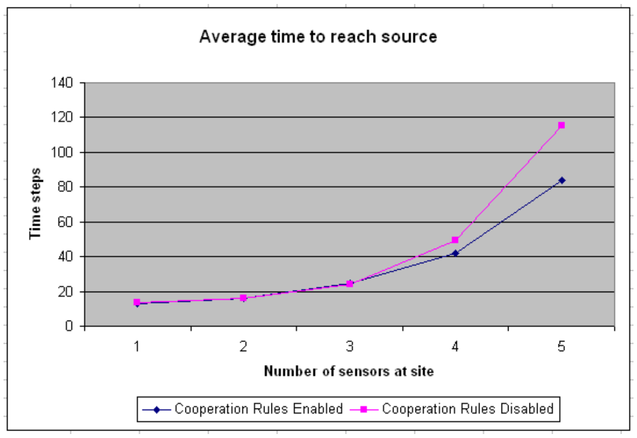

Figure 4: Results showing number of steps to find source.

Cooperation Rules	1st arrival	2nd arrival	3rd arrival	4th arrival	5th arrival
Enabled	13.1	15.76	24.76	41.86	84.1
Disabled	13.6	16.1	24.13	49.4	115.63

Table 1: Average steps to reach the source.

Our results show that the cooperation rules lowered the number of steps required to find the source. Without the cooperation rules, we found that some of the mobile sensors would wander around searching in the opposite direction of the source. In this case, the number of steps to find the source was much higher.

With the cooperation rules enabled, we observed that it took fewer steps for the mobile sensors to find the source. This was apparent when more mobile sensors were used. Once a gradient was found, the position was communicated throughout the network. This enabled wondering sensors to reposition their movement toward the source. This caused a pulling effect, forcing more sensors to search the event area. Once a higher gradient was found, the cooperation rule communicated the information again. This process repeated until all sensors found the source.

Table 2 shows the range of steps required to find the source. We found that with the cooperation rules enabled, finding the source was more reliable.

Cooperation Rules	1st arrival	2nd arrival	3rd arrival	4th arrival	5th arrival
Enabled	12-15	13-22	19-35	24-109	30-145
Disabled	12-17	12-26	19-81	21-248	25-276

Table 2: Range of steps to reach source

The standard deviation is shown in figure 5 and table 3. As in the range, this shows more reliable results when the cooperation rules are enabled.

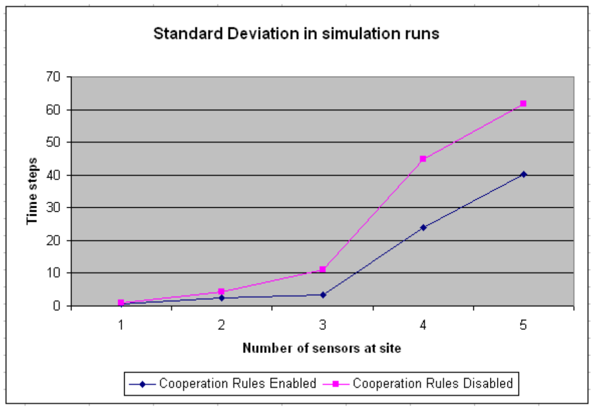

Figure 5: Results showing standard deviation of the simulations

Cooperation Rules	1st arrival	2nd arrival	3rd arrival	4th arrival	5th arrival
Enabled	0.66176	2.4731	3.4709	24.077	40.345
Disabled	0.93218	4.1882	11.048	44.822	61.823

Table 3: Standard Deviation in reaching the event in steps of time

The overall results show that there was very little difference between the two sets of data as to how long it takes the first, second, and third mobile sensor to arrive at the source. However, the differences in the arrival times of the fourth and fifth mobile sensor are significant. We used the Student t-test for comparing the difference between the means of the five mobile sensors. We calculated the t value for each pair, comparing the values of the mobile sensor with the cooperation rules enabled and with it disabled. Our results showed that mobile sensor four had over an 80% confidence level and mobile sensor five had a significant difference over 95% confidence. This supports our conclusion that the cooperation rules result in fewer steps for mobile sensor four and five to find the source in our simulations. The savings in steps can be directly converted to savings in energy that can be used for other purposes.

6. CONCLUSIONS AND FUTURE WORK

Animals have adapted to live in nearly every part of our environment. Mimicking characteristics of the pill bug has provided a starting place to define swarming behaviors for our simple, mobile sensors. Our research takes inspiration from the pill bugs characteristics, including locomotion, sensors, and behavior. Our findings show that the kinetic behaviors of the pill bug provide a sufficient rule set for swarming using mobile sensors.

We plan to enhance our scheme by introducing new behavior rules and additional metrics. We are researching efficient and reliable methods to support the cooperation rules on resource constrained hardware platforms.

7. ACKNOWLEDGEMENTS

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