Ant colony optimization based swarms: Implementation for the mine detection application

Vignesh Munirajan
Ferat Sahin
Eric Cole

Follow this and additional works at: http://scholarworks.rit.edu/other

Recommended Citation

This Conference Proceeding is brought to you for free and open access by RIT Scholar Works. It has been accepted for inclusion in Presentations and other scholarship by an authorized administrator of RIT Scholar Works. For more information, please contact ritscholarworks@rit.edu.
Ant Colony Optimization based Swarms: Implementation for the Mine Detection Application*

Vignesh Kumar Munirajan
The Advanced Technology Research Center
The Sytex Group Inc
vkumar@atrc.sytexinc.com

Dr. Ferat Sahin
Dept. of Electrical Engineering
Rochester Institute of Tech
Rochester, NY, 14623
feseee@rit.edu

Dr. Eric Cole
The Advanced Technology Research Center
The Sytex Group Inc
ecole@atrc.sytexinc.com

Abstract - Mine detection is a sensitive task confronting the battlefield strategists. There is an ever-increasing demand for proper and sophisticated resources for many issues involved in the task. Traditional practices still involve human force directly in executing the tasks in spite of the advances in technology for tools and implements for the operation [1]. The problem includes various facets inherently: two of the prominent issues are location of mines over a minefield and secondly removal of the mines once located [1]. These two issues are not totally independent as technology used for one can directly or indirectly affect the other. Recent developments in artificial intelligence, natural heuristics, computational optimization and robotics have endowed us with the ability to realize unmanned robots (or robot like vehicles) that work intelligently on a real time basis in attempting at the problem of mine detection. In this paper we focus on the algorithms developed using ant colony optimization based approaches to the mine detection application and its implementation on a real-time basis. We focus on certain optimization techniques that could be used for effective realization of the algorithm. Generic groundscout robots had been already built at the MABL, RIT [12]. These robots have been used to demonstrate the implementation.

Keywords: Swarm Intelligence, Mine Detection, Collective Robotics, Ant Colony Foraging, Natural Heuristics

1 Introduction

Mine detection requires a global algorithm, when the question of how robots can be allowed to apply for the task arises [1, 2]. The mine detection algorithm becomes an optimization problem with various parameters. Some of these parameters are total coverage of the terrain involved, complete removal of the mines present on the terrain, and time involved for the total process of demining. Trends in artificial intelligence can be scenarios where most optimization problems are dealt with successfully [2]. One such scenario is heuristics and intelligence assembled from the field of swarm intelligence, and it can be used in posing a solution to the task of mine detection. Swarm intelligence is a highly established area of research in natural heuristics particularly aimed at applications in combinational optimization [2]. Natural foraging and terrain covering models are well-defined and implemented using swarm intelligence successfully. The mine detection problem is a very interesting application for the study of swarm intelligence.

In our previous works we have attempted to establish an approach based on swarm intelligence for the mine detection problem [3, 4]. Both the aspects of location of mines over the minefield and demining by coordination were addressed. The action of locating unknown randomly distributed mines (which we call navigation or mine-foraging) over a minefield was inspired by cognitive map based on swarm foraging (anti-colony). Collective demining was addressed using approaches based on recruitment procedures (Short Term Recruitment-SRR) normally observed in ant colonies during navigation [2]. Stagnation recovery means disentangling from deadlocks and cyclic loops during the course of the process of mine detection. We observed that such a scenario that we have termed as freezing, is a normal occurrence when the robot-mine ratio is less [3, 4]. We have proposed a solution at the global level intelligence to avoid the unwanted phenomenon from occurring. Most of the above-mentioned scenes are only at the simulation level. We wanted to put up a real time platform for observing what are the challenges and issues occurring when such simulation level models are put in practice. We have used the Cooperative Autonomous Robots as a platform for observing our results [4].

2 Ant Colony based Foraging

Navigation in ants is a task involving coordination of nestmates. The basic means of communication during navigation among the individuals of an ant colony is by the laying of pheromone trails. Pheromones are special chemical substances secreted by the ant during their motion so as convey information that it has followed a particular route. Pheromone concentration has the ability to decay (evaporate) with time. Ants tend to follow routes rich in pheromone concentration. This aspect of ant motion...
was investigated by researchers in most ant species and has been applied to most practical and optimization problems [1, 2, 3, 4, 11]. The famous traveling salesman problem (TSP) and the quadratic assignment problem are examples where pheromone trails of ants are used for solution. Routing in communication systems is another important and interesting application where ant based optimization algorithms has been successfully applied.

Though much of literature regarding ant navigation has a pheromone-based approach, other means of ant navigation methods also exist in literature. The use of Cognitive or Visual Cues (terrain and celestial cues) by ants during navigation has been reported in *Polyrhachis laboriosa* or tree dwelling ants [2, 3, 4, 11]. In this type of motion, seen in certain ant colonies, visual cues acts as a means of communication. Individuals evaluate their position with respect to certain known coordinates (usually the nests) with the help of visual cues. This can be done in two ways: path integration and the ability of the ants to remember positions of them during motion. In our application of mine detection, we have applied such type of foraging behavior to the ants, which obviates the use of pheromones for their motion.

Navigation in ants is normally a collective activity. Two main modes of navigation are observed in ant colonies. In the first mode a certain chemical called pheromone is secreted all along the path an ant travels. These pheromones act as bacons for followers or others to decipher their future enroute [2]. Ants gather their nestmate’s pheromone trail information to devise their future foraging or navigational strategy. Certain ants, as they return to the nest with food, lay down a trail pheromone [2]. This trail attracts and guides other ants to the food. It is continually renewed as long as the food holds out. When the supply begins to dwindle, trail making ceases. The trail pheromone evaporates quickly so other ants stop coming to the site and are not confused by old trails when food is found elsewhere. A stick treated with the trail pheromone of an ant can be used to make an artificial trail with is followed closely by other ants emerging from their nest. Other ants will not maintain the trail unless food is placed at its end. In the second mode, an organizational map of visual cues or visual information is collected during foraging, which may be utilized to embark on future routes. Mostly this method is resorted to when ants follow up food particles to their nests.

Any point in space can be specified by its location from an infinite number of other points. As a consequence, there are numerous choices open to an ant when attempting to remember the location of a goal. Constraining the choices of ants are physical properties of the natural environment. For example, short landmarks will tend to become obscured by intervening objects, so we expect that ants will tend not to remember them (Bennett, 1993a), and under some circumstances we would not expect the ants to remember moving landmarks (Bennett, 1993b) [2]. Also constraining choices are probable limits to the total amount of spatial information that can be remembered. For this reason, there are likely to be trade-offs between the number of landmarks used to remember the location of each goal, the accuracy with which each goal is remembered and the number of goals that can be remembered. Clearly then, as an ant moves around in its environment, it is faced with numerous decisions about the type of spatial information to remember. Two processes can be distinguished. The first involves decisions about the types of landmarks to remember. The second concerns the geometrical properties of space that are specified by the remembered landmarks. In the following section we analyze how the generic cooperative autonomous robots are designed to work as cooperative ants for the mine detection task.

### 3 Mine Detection Algorithm

The approach that we have used for the mine detection problem is a combination of both deterministic and stochastic methods. We bring in the stochastic component only in the foraging stage, while the stage when an ant enters a scent area it does not behave stochastically, but rather in a deterministic manner. It simply follows the route, which has an increase in the scent, and since the intensity of the scent supposedly peaks at the mines, the ant eventually finds itself at the mine.

An important concept that has to be observed during the process is when all of the ants go into the state of waiting for the others the come at the respective mines. Factors leading to this can be the field size, the initial distribution of the mines etc, and the ratio of the number of ants deployed to the mines present. Such a situation can be called freezing, where there is no motion of the ants and all of the ants are waiting infinitely for the others [2, 3, 4].

The tables below shows a detailed description of the ants’ behavioral model in terms of behavioral change conditions and reactions:

- **Behavior 1- Foraging**
- **Behavior 2- Trail Following**
- **Behavior 3- Waiting**

<table>
<thead>
<tr>
<th>No.</th>
<th>Behavior Change</th>
<th>Conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Behavior 1 to</td>
<td>When a foraging ant detects</td>
</tr>
<tr>
<td></td>
<td>Behavior 2 to Behavior 3</td>
<td>Behavior 2 to Behavior 1</td>
</tr>
<tr>
<td>---</td>
<td>--------------------------</td>
<td>--------------------------</td>
</tr>
<tr>
<td>2.</td>
<td>When an ant follows a scent concentration to a mine</td>
<td>When the maximum of the scent intensity around becomes zero</td>
</tr>
</tbody>
</table>

### 4 Optimization Strategies

In context to the mine detection a basic foraging strategy (minimize the time taken by the agents to detect all of the mines) has to be devised. Here we assume that the number of mines is a very small percent of the field size. This assumption emphasizes the fact that a large amount of time spent by the agents is on foraging (checking for the presence of a mine). Therefore if we were to devise a basic foraging strategy we conserve a lot of time on the whole process.

In the process the agents, during their foraging period always move towards a randomly generated point on the field. Basically, the ants can have an apparent mapping of the field into a certain number of regions, which can equivalent to the cognitive maps or the visual cue information that the ants are capable of having. An ant can randomly generate a point in a randomly generated region and move towards the point in a deterministic manner or perform a random walk towards the point. For our analysis we have considered the deterministic nature of ant movement. The deterministic movement towards the point is two fold, first along one axis then along its perpendicular axis. During this motion if they come across a mine or enter into a field of scent they change their behavior. An ant's motion along one direction is independent of its perpendicular direction. Let us consider the one-dimensional case and extend it the two-dimensional case utilizing the fact of independency.

Let us begin the analysis with the calculation of the probability of any point on a one-dimensional line. Initially the agent is at one end of the line. It randomly generates a point on the other half of the midpoint of the line and starts moving towards the point. After reaching the point it randomly generates a point on the first half and moves towards it. This process, which is similar to a random walk, is repeated continuously. In this situation the probability of a point being visited by the ant is given as follows.

Since the random point generation is symmetric about the midpoint, we can consider each of the halves separately for the analysis. Let us consider each half to be of length $a$ and $x$ the distance of the randomly generated point from the midpoint of the line. The probability that an agent per unit time visits a point is as follows.

$$P = 0.5 \int_{x}^{a} f(x)dx \quad (1)$$

where $f(x)$ is the distribution by which the points are generated.

Extending to the two-dimensional case we get

$$P(x, y) = \left[ 0.5 \int_{x}^{a} f(x)dx \right] \left[ 0.5 \int_{y}^{a} g(y)dy \right] \quad (2)$$

Let us assume that the points are generated uniformly on either side of the midpoint. Therefore $f(x) = \frac{1}{a}$ for $0 < x < a$

This gives that

$$P = 0.5 \int_{x}^{a} dx = 0.5 (\log(a) - \log(0)) \quad 0 < x < a \quad (3)$$

A quick check reveals that $\int_{0}^{a} Pdx = 1$

For the two-dimensional case

$$P(x, y) = 0.25(\log(a) - \log(u))(\log(b) - \log(y)) \quad (4)$$

An assumption that we make here is that the best foraging strategy could be devised if we find a function $f(x, y)$ for which the distribution $P$ is the same as the distribution of
the mines over the field. Finding $P$ demands the following equation to be solved

$P$ given

\[ f(x) = \int_{0}^{a} f(x) \, dx \int_{0}^{b} f(y) \, dy = h(x, y) \quad \text{(5)} \]

Using the fact that $x$ and $y$ are independent, the above expression in the two-dimensional case could be reduced to the one-dimensional case. Therefore the expression reduces to

\[ 0.5 \int_{x}^{a} f(x) \, dx = h'(x) \quad \text{(6)} \]

where $h'(x)$ is the marginal density of $h(x, y)$

Differentiating the above expression on both sides with respect to $x$

\[ \frac{d}{dx} \left( 0.5 \int_{x}^{a} f(x) \, dx \right) = \frac{d}{dx} h'(x) \quad \text{(7)} \]

Let $\int_{x}^{a} f(x) \, dx = F(x)$

\[ \frac{d}{dx} (0.5(F(a) - F(x))) = \frac{d}{dx} (h'(x)) \quad \text{(8)} \]

\[ -0.5 \frac{d}{dx} F(x) = \frac{d}{dx} (h'(x)) \quad \text{(9)} \]

\[ f(x) = -2x \left( \frac{d}{dx} h'(x) \right) \quad \text{(10)} \]

The above expression gives a representation for the manner in which $f(x)$ in the one-dimensional case behaves. Since we assume that the movement of the ants is independent along the two dimensions of the field, an extension of the above result for the two-dimensional case can be easily carried out. The main point to be noted is that for $f(x)$ to be a probability distribution function the differential of the marginal density function of the mine distribution should have negative slope on either side of the midpoint of the one-dimensional line. Further care should be taken that $f(x)$ integrates to one to be a valid probability distribution.

When the distribution of the mines is not known beforehand, the assumption of it being uniform can be made. Unfortunately a closed form solution for $f(x)$ does not exist for the uniform distribution case. This is true for many other distributions too. But in all of the cases a discrete approximation can be made for $f(x)$ to suit the particular distribution since the field is normally discrete.

5 Cooperative Autonomous Robots

The Cooperative Autonomous Robots (CAR) or groundscouts robots were designed to demonstrate multi agent capabilities at a more practical level [12]. The architecture and design of the cooperative autonomous robots was carried out as a part of the ongoing research activities at the Multi Agent Biorobotics Lab, EE, RIT [3, 4, 12]. The cooperative autonomous robots are an ensemble of many features in robot capabilities. The features included a locomotion layer, a power layer, ultrasonic, proximity and infrared sensors, a control layer and an intra robot communication layer. The robots were designed to be modular and are programmable to suit any target application. Some of the applications for which the cooperative autonomous robots can be programmed include surveillance and security, mine detection, reconnaissance, search and rescue missions. The present cooperative autonomous robots are in the third generation robot architecture. The entire design of the second generation and the first generation was overhauled to construct the third generation and present groundscout architecture. Prominent changes to enhance the functionalities of the robots were included in the third generation architecture. The entire design architecture of the third generation cooperative autonomous robots was divided in a number of component layers. Each layer was responsible for a group of individual functions, which would be collectively organized and controlled by the control layer. The individual layers that form the architecture of the robots are given as follows.

- The Locomotion Base
- The H-Bridge, Proximity and Power layer
- The Ultrasonic layer
- The Infrared layer
- The Control layer
- The Communications layer

Table 2. Reaction produced on behavioral changes
The robots were designed to forage for mines over a minefield. The obstacle avoidance and mine sensing routines run parallel to the foraging routines. When a robot is successful in detecting a mine it stops foraging and goes into a state of waiting until four of them are found at the minefield. The mines were programmed to emit infrared waves detectable by the receivers in the infrared layer.

Successful results were obtained both at the simulation level and the emulation level employing these robots for mine detection. Additional advantages could be made by utilizing the communication board for inter robot communication to make the system more effective. Intra robot communication data could be information containing mine locations, scent distributions and others that are aimed at improving the performance of the system, as a whole. Though the results were successful in demonstrating the ability of the robots executing the mine detection task, we had a variety of difficulties in bringing up the system to works. Some of these problems speak for the complexity that poses when a decision is made to transform a simulation level algorithm to real time implementation particularly in distributed computing. In essence the mine detection task is highly complex at practical levels and requires a high degree of precision and suave resources for implementation.

The infrared layer was used to sense the mines over the minefield. The mines were programmed to emit infrared waves detectable by the receivers in the infrared layer. The signal that the mines would transmit was defined to be a 900 Hz square wave modulated over a 38 KHz carrier. The ultrasonic sensors are employed to detect obstacles and other passing robots. The ultrasonic sensors have the ability to estimate distance of any obstacles, which can obstruct the path of the robots. The control layer houses the microcontroller and the application program and the control of the various layers.

### Issues and Analysis

The first major problem that a practical scenario would be experiencing is that of how to evaluate the life time of the ants involved in the mine detection process. In our evaluation we equipped the robots with finite life batteries which are expected to power up the whole robot during the entirety of the operation. But this could be a very fragile expectation, as we found in our analysis from the CARs that gradual weakening of the robots could cause the robots to come to an absolute halt abruptly. This could result in a temporary or permanent loss of the robot. A means that could monitor battery life and reflect its condition for adequate changes should be incorporated in the system. Not only was the danger of losing the robot’s life, but some of the functionalities that the robot carries can be affected by battery weakening. When open loop operations are run in the system loop parameters are not modified explicitly by feed back, in which case operations are performed based on environmental parameters. One such environmental parameter which is unpredictable is battery life. Software fixes can be made to rectify such errors, but it would instead have constraints on the sensory abilities of the robot. Thus it is very important to have a balance between complexity and robustness of the system.

Another important issue that erupted during the analysis was sensory and actuator issues. The CARs were very good in terms for actuator abilities, but were limited by the sensory abilities for a complex application like mine detection. The CARs were equipped with infra red sensors, proximity sensors and ultra sonic sensors. The demonstration uses the ultra sonic sensors to sense obstacles and distance, the infra red sensors and proximity sensors to detect the presence and absence of mines. The ultra sonic sensors were positioned in the front of the robots one in the center and two others positioned at 45 degrees on either side to the one on the center. The basic problem with the ultra sonic sensors was the cone angle it had for both transmission and reception.

The demonstration provides us incite into a lot of similar aspects that the mine detection process can carry when attempted in a real time basis. Robust software and competent hardware are an absolute necessity for practical realizations. This is a first step in moving in towards practical realization of employing only robots for the mine detection process. The potential issues that could arise when such a step were to be taken has been logged and
remedial measures to address them would be contemplated in future research.

7 Future Work

There are certain areas where the present work could be improved on. The time required completing the detection of the mines in the region, can be reduced if the ants use the information of the mines that it has detected in deciding on the future foraging strategy [8, 9]. Improved results can be obtained if the ants adaptively change their map (the division of the foraging region into distinguishable regions) of the foraging area in accordance previously defused mines. Also the algorithm could be applied to scenarios where the mines can be mobile. Simulations can be performed in situations where the nature of the mines can be different and demand a defusing technique different from the rest of the mines.

8 Conclusion

We have realized a real time platform for demonstrating our proposed approach of the swarm intelligence based mine detection algorithm. Without a study conducted on a real time basis any algorithm would have serious implementation difficulties at the practical level. The difficulties are easily compounded when dealing with sensitive issues like mine detection. Analysis conducted with the help of the cooperative autonomous robots certainly enhances the validity of our algorithm at a more practical level. We would like to evaluate the performance with more enhanced functionalities of our cooperative autonomous robots in future. Future incorporations like a GPS layer for the cooperative autonomous robots would add to such increased functionalities [3, 4]. On the other hand the analysis is an astounding forum for establishing the fact that complex entities are not a requirement for approaching optimization problems, which is a core aspect in distributed artificial intelligence.

Acknowledgement

This research was done under the able guidance and support from The Multi Agent BioRobotics Lab and The Advanced Technology Research Center, TSGI.

References


