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A Swarm intelligence based approach to the mine detection problem

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***Abstract*—In this paper, we have applied a swarm intelligence based technique to a mine detection problem. Swarm intelligence techniques are used to model robotic agents to solve the problem. Studies made on the ant colonies, which is a typical member of the family of swarms, are applied in devising the techniques for the agents. Ant colony models bestow intelligence not only at the individual level, but more at the collective level (the interactions produced byt he individual members in trying to solve a common problem). An analysis of the results obtained with a computer simulation of the mine detection is also presented.**

Keywords: **swarm intelligence, mine detection, ant colony, foragingr ecruitment**

I. INTRODUCTION

Swarm Intelligence is a branch of artificial intelligence, which deals with the exploration and study of animal behavior and its effective utilization on real time and intelligence based problems. Explorations of animal behavior begin with the observation of the animal's living characteristics and conditions, and collecting information on their response to the routine needs of their life. Various features of animal behavior, as their life style in a particular environment, coordination among peers, foraging for food etc, are observed. In this regard, swarms, which basically comprise a major portion of the insect community, certain forest herds, birds etc, are extensively studied [1, 2, 3]. Applications of swarm intelligence have been found in many fields and are constantly expanding [2, 8]. An *Ant Colony* is a rigid and compact member of the swarm community, as it exhibits almost all the characteristics and diversities that are observed in swarms [1, 2].

In this paper we tried to build agents with intelligence derived from the concept of swarm intelligence for the problem of mine detection. Mine detection has been a task of military intelligence for ages. The traditional method of using sniffer dogs for mine detection is tedious and risky. In this paper we tried to develop artificial agents that can forage the marked area of mines and collectively defuse the mines. The main aim of thep aper is to bring about coordination among a group of mobile individuals who are assigned the job of mine detection. In certain instances like real time battlegrounds the amount of time taken by the agents in defusing all of the mines in a given region may be critical. We also propose to give certain strategies for the agents based on principles of swarm intelligence. We make certain assumptions (as the knowledge of the distribution of the mines over the field etc) in making the above-mentioned proposal. The organization oft he paper is done as follows: Section 2 discusses social insects as a member of the swarm family. Section 3 discusses the ant colony, a member of sociali nsects, as a full-fledged component of swarms and the application of itt o the mine detection problem. Section 4 describes the experimental set up for the mine detection problem and the assumptions made for the simulations. The analysis of the problem with the swarm intelligence approach and the results obtained are shown in Section 5.

II. SOCIAL INSECTS

An important branch of swarm intelligence is the study of social insects. Social insects are characterizedb y *self-organization* [1,2]. Self-organization is the feature by which simpler actions of individuals can be reinforced at a collective level, which can be complex. The basic reason for the colony to function on theories based on self-organization is that individual complexity need not be invoked to explain colony level activities, though this may always not be the case. Self-organization is observed mainly in ant colonies, honey bees, certain colonies of locusts etc. Intelligent system design can be viewed as an exercise for which concepts of selfo rganization can be applied at the global level. Practical problems in engineering can be solved with more flexibility and robustness with this approach [2]. Self-organization is based on amplification of random fluctuation of individuals. Individuals always have a very low probability of error in performing the required task, which in a large colony, at certain instances, is amplified to produce new routes of exploration [2]. Another important concept in selfo rganization is

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emergent behavior [2]. Emergent behavior is the phenomenon where a particular complex colony level organization is constructed by individual manifestations of behaviors on the environment, which gradually evolvesi nto the complex structure at the colony level organization. An example for such type of behavior exhibition is the process of nest building in wasps and ants [1, 2]. Communication among the individuals is a note able feature in social insects. In an ideal case, for perfect coordination at thei ndividual and the colony level to be realized, inter group and intra group (assuming the colony is divided into apparent groups at various levels, which is the case in most of the ant and wasp colonies) communication is most essential. In most colonies a form of communication among individualsc an be seen which is called *stigmergy* [2]. Stigmergy is the process of individual-to-individual or group-to-group communication in which certain manifestations in the environmenta cta s the medium of communication. This manifestation can be a physical manifestation or a reorganization of the individual's activities for others to follow. Such type of manifestations is observed in the laying of pheromone trails of ants nest buildu pi nw asps etc. All of the above-mentioned phenomena are strongly seen in ant colonies. In the following section we discuss the colony system in ants and its manifestation of the features mentioned above.

III. THE ANT COLONY SYSTEM

A major branch of Swarm Intelligence ist he study of Ant Colonies. Ant Colonies are well-coordinated and well-organized entities that show a bottom to top approach without a rigid hierarchy. Individual manifestations of stimuli and responses are in response to local problems, which grow collaterally to solve the complex global problem. The major feature of the ant colony system is the absence of central control. All of the ants are assumed to have absolutely no or very little means of direct communication among themselves, yet they have the responsibility of carrying out the routine tasks oft he colony system. Deneubourg's model of the ant colony emphasizes positivef eedback obtained by individuals reinforces the ability of the ants to interact at the colony's hierarchical levels [2]. The application of the ant colony system to the mine detection problem may require a two-fold approach. First, an effective foraging strategy fort he agents should be devised, that is a means of agent movement over the field of mines so as to detect the presence of a mine at a particular place over the field. Secondly (in certain instances), a mechanism for recruiting other agents foraging over the field or placed on reservea t a particular spot to the point of detection so as to defuse the mine collectively, has to be devised. The second case may apply to situations, where the strength of the mines may be unknown and requires ap articular number of agents, depending on the particular mine to be defused. In situations, where a mine detected by an agent can be diffused by the combined action of more than one agent, the second case will apply. We formalize a strategy based on visual cues/path memorization for the foraging part of the problem [4, 5, 6]. Foraging strategies based on these phenomenonsh ave not been explored a lot in present literature. We based our presentation in which the agents (equivalent to ants searching a terrain for food), have the ability to remember the spot (over the field), which they are foraging which respect to certain fixed coordinates [5, 6]. We also consider the aspect of recruiting (if needed), to bring about the diffusing of am inei n a collective fashion. We shall discuss the process of recruitment in the following section.

Collective transport is a complex phenomenon in insect colonies that involves detection and physical transportation of object (mainly food particles, brood, etc.) from one location to another. Collective transportation not only involves these basic concepts, but is actually complicated when features like coordination in collective movement, and stagnation recovery are involved. One of the main aspects of collective transportation is the study of cooperative prey retrieval in ants. Cooperative prey retrieval is the act of finding the prey, deciding on how it can be transported to the destination (nest) and thep hysical transportation of it to the nest. Certain questions that arise regarding the collective transportation problem are given as follows [2].

- How does an ant know that the object ist oo heavyf or it to lift alone, and has to recruit nest-mates to start collective transportation?
- How is it able to attract nest-mates when help is needed?
- How do theyc ome to know about ther ight number of ants to start collective transportation?

The process oft ransportation begins with the detection of the prey by a single, or a small group of ants. At this point a decision has to be made as to whether the object can be lifted or pulled by the detector alone or whether some more of the nest mates havet o assist. In most cases the main factor, which leads to group transportation, is the weight of the prey [2]. A solitary anti nitially tries to realign itself and the prey to test for solitary transportation. When solitary transport turns out to be futile, group transportation is resorted. Other factors that can lead tog roupt ransportation are the prey's resistance to motion, and the preference of the prey. In *Pheidole pallidula*, it was observed that it was the resistance to traction rather than the weight of the prey itself that was responsible to invoking group transportation [2]. We can thus see that it is the manifestation or accumulation of individual's inability in execution of the task that is responsible for group's responsive patterns towards the task change.

Recruitment of nestmates is the process of attracting nestmates when an ants ucceeds in detecting a prey and after certain attempts determines that solitary transportation is not possible. Holldobler showed that in the species of *Novomessor* (*Novomessor albisetosis* and *Novomessor cockerelli*) two distinctive processes were involved in the process of recruiting [5]. In the first process the ant, which detects the prey, spreads a scent around the prey, which attract the ants present in the local vicinity oft he prey. This is called short-range recruitment (SRR). In most cases the concentration of the secretion decreasess patially. It wasa lso observed that as time progresses the number of ants following the scent decreases, which may be due to the scent evaporating or to allow for some other effective techniques to be followed by the ants that has detected the preys o that collective transportation is possible. SRR is followed by long-range recruitment (LRR), a process wherein the ant, from the point of the scent to the nest, lays a pheromone trail so that other ants may follow to assist in collective transportation. It was shown by Holldobler that LRR isu sed only when the inability of the group of ants in moving the prey accumulates over time [5]. How an ant resorts to attracting other ants around it, or int he ant colony, gives us important clues on how coordination in a collective system can be achieved. The important point to be noted here is that there is no physical communication involved in this process. The basic phenomenon ofp roducing changes in the environment, which acts as a beacon for the others to follow, is exhibited here (stigmergy). This kindo f behavior is also noted in the case of defense strategies in an ant colony system [5]. Whenever one or a group ofa nts in the colony finds an imminent foreigner they resort to scent spreading as a means to attract others in the colony. In this case the time allocated for SRR is very short when compared to the case of prey retrieval. The basic aim of the coordination mechanism is to bring the optimal numbero f ants to the point of action. We may see the scent concentration decreasing as more and more ants are recruited for action. Mainly the number of ants required is decided on the size of the prey to be retrieved. As the concentration of the scent decreases one can see that the tendency of the ants reacting towards SRR is reduced, which may acta s an incentive for LRR to begin.

IV. THE MINE DETECTION PROBLEM

By the mine detection problem, we mean the problem of detecting and defusing randomly placed mines over a field. We assume that the agents (ants), which are deployed to defuset hem ines, aree quipped with the ability tod etect the mine whent hey approach them physically. The defusing of the mines demands the collective actiono f a certainn umber of agents. The agents are simple and are assumed to be non communicative. The main goal of the work is to eliminate the central intelligence in driving the agents for the completion of the task.

We tried to model the problem in accordance to thato f a collective transport problem found in ant colonies. We assume that the minesa re tantamount to the prey that thea nts, which are all identical in behavior and movement, have to detect over a field area. We give the ants a foraging strategy in order to scout for the mines. When an ant reaches a mine it spreads a scent around the mine in resemblance to SRR found in certain ant colonies. This scent decreases exponentially in a region around it. The spread of the scent is equivalent to physical stigmergy, which are basically physical changes produced int he environment so as to bring about a desired reaction, in this case attraction of other ants around the mine to the mine. The ants around the mine follow the scent's increasing gradient and finally land themselves at the mine. We should note that the ants would not lose their foraging behaviore ven when they are intimated by the scent about the presence ofa mine in the locality. Thus the mine would be eventually defused when the required number of ants arrives at the mine's location. The decision on the number ofa nts to defuse a particular mine, may be done by the first ants detecting it. The problem is modeled in such a way that the attraction of the required number of ants is prefixed and not at the location of the mines itself, so the aspects of deciding on the number of agents to defuse a particular mine and transportation of it, is not important.

Some of the vital aspects involved in the problem is the guaranty that a mine is completely defused and that of the time that the ants take in defusing all of the mines over a given field size. We assume that the field size over whicht he mines are distributed and number of mines that has to be defused is known. This eliminates the problem of assuring that all of the mines are detected, though the time taken for defusing all of the minesm ay need to be minimized in certain instances. This may require a good foraging strategy; though increasing the number of ants deployed, can minimize the time taken for defusing the mines. We have given a probabilistic strategy for this case. The strategy that can be employed and the assumptions needed for it are detailed in the following section.

IV. THE ALGORITHM

In the context of mine detection a basic foraging strategyh as to be devised. Here wea ssume that the number of mines is a very small percent of the field size. Thisa ssumption emphasizest he fact that a large amount of time spent by the agents is on foraging (checking fort he presence of a mine). Therefore if we were to device a basic foraging strategy we conserve a lot of time on the whole process. The ants have three distinct behaviors during the whole process. They are *foraging*, *scent following* and *waiting* modes. The agents, during their foraging period always move towards a randomly generated point on the field. Basically, the ants can have an apparent mapping (cognitive maps or visual cues) of the field, with respect to fixed coordinates (the boundaries of the field) into a certain number of regions. An ant can randomly generate a point in a randomly generated region and move towards the point. The movement towards the point is two fold, first along one axis then along its perpendiculara xis. Research on tree dwelling ants *Polyrhachis laboriosa* suggests this type of movement, where ants are able to remember locations on the terrain and may moved irectly towards it [6]. 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 isi ndependent of its perpendicular direction. The following figure shows the deterministic movement in going from one, the originating location to the other, the destination.

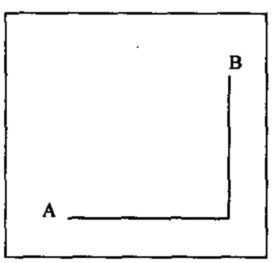

Fig 1. Movementf rom points A to B in a deterministic way

In another scenario, the ant's movement can be a random walk to the destination point (the point where it has to reach. The random fluctuations produced by the random walk can be controlled when the ant reaches the axiso f one of the coordinate of the point. During the random walk the ant moves one along the two directions that are towards the destination that it has to reach, in direction.

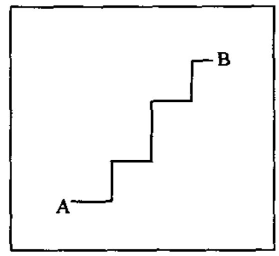

Fig. 2. Random walk from point A to pointB

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. During the scent following period, an ant simply follows the route, which has an increase in the scent, until the intensity of the scent peaksa t the mines, the ant eventually finds itself at the mine. Whena na nt detects a mine it enters the waiting mode till the required number of ants arrive for defusing the mine.

When the mines are densely concentrated over the field, there may be instances where two or more scents can overlap. Ins uchi nstances, the algorithm should ensure that the peak in scent intensity occurs at the mines and that not many of the foraging ants entert he overlap region. The overlap region (formed by the overlap of two or more scent spread areas, when mines that are quite closer to each other get detected by independent ants, at almost the same time) is normally very complex in terms of the scent distribution in it. It depends on dynamic quantities like the number of overlaps that have occurred at a particular time and the extent of the scent concentration spread. There can be a possibility of local maximas in terms of the scent concentration in the overlap region. The occurrence of local maximas in the region would be a function of the two features mentioned above in addition to the exponent chosen for constructing the exponential fall of the scent. Local maximas could be detrimental because when an ant encounters a local maximum it will be halted at that location, as its behavior within the scent-spread region would be only the following of increasing concentration of the scent. This may lead to the temporary unavailability of the ant for mine detection. This would not cause a false alarm, as the behavioro f the ants inside the scent-spread region is both "following the scent gradient" and "check for mines on its path". Once the respective mines, which are responsible for the overlap are defused the local maximum disappear and the ant would resume its normal functions. Thus, though the ant will be temporarily unavailable for the task, this time is short-lived.

For the spread of the scent we use a falling two-dimensional exponential curve. The exponent has to be less than 1, in the case when we use integers for raising the exponent. This may be good enough when there is no overlapi nt he scent regions, but whens ituations arise where there can be overlaps of thes cent field, care should be taken in fixing the exponent for the scentd istribution. In cases of overlap of scents, we add the scent intensity at each point to bring about the combined scent concentration in the overlap region. We have to make sure that in adding up the intensities, we do not create a situation wherein an ant foraging outside the overlap region enters the region. The method we adopt for achieving this is as follows.

Let us use an exponent named a for the scent distribution. Thus the scent distribution (S) goes along each axis $S = a^x$, where x can take integer values from 1 to m, with m being the last value, on eithers ide of the mine. For allo f the above constraints to be satisfied we should pick up a which satisfies the following condition.

$$a^{x+1} + a^{m} < a^{x} \quad (1)$$

For this condition to be valid, the value for a should be a number which is in the range 0 and 0.5. Thus we see that for two overlaps the range of values that the exponent can take becomes narrower. Thus the concentration of the mines poses a constraint in the value that the exponent of the distribution can take. The problem of analyzing the regions with more than one overlap grows exponentially with the number of overlaps. Witht his criterion the ants that happent o touch the outerb oundary of the overlap region tend to move away from the region rather than moving into it.

V. Simulation Results

The simulations were conducted over field sizes of 100x100 and 50x50 to observe the features of the algorithm. Simulations were run for various combinationso f number of minesa nd number of ants foraging for defusing them. The number of ants required to defuse a mine wasa ssumed to be four. In the simulation the visual mapping of the field for every ant comprises the four quarters of the rectangular field. The following figures show the results obtained for the various runs against the time required for all of the mines (uniformly distributed over the field) to be defused. A feature observed on the simulations was that there were instances when all of the foraging ants end up at the mines and wait for each other infinitely. Such a situation results in a dead lock where none of the ants move and continue to remain in the state infinitely. Such a state is denoted as a *frozen* state.

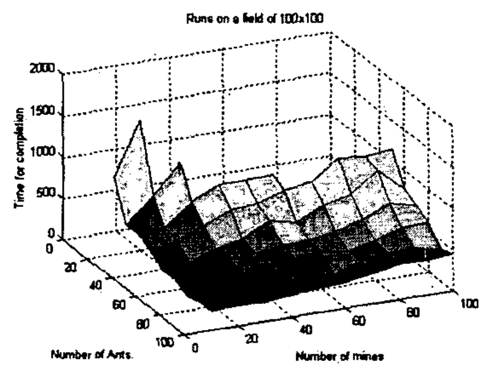

Fig 3. Results for runs on a 100x100 field with deterministic motion

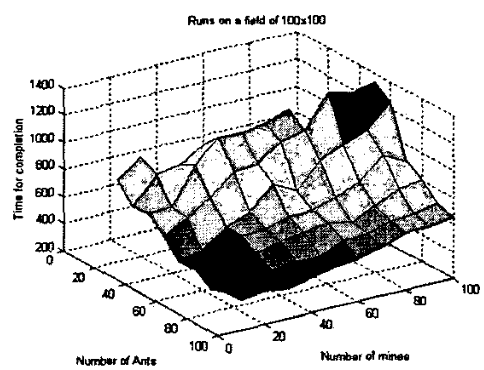

Fig 4. Results for runs on a 100x100 field with random walk

From the results we can observe that as we increase the number of ants deployed for detection the time required for the process to be completed decreases. A study was also conducted to find the minimum number of ants (on average) required to avoid freezing. A plot showing the observations is given below

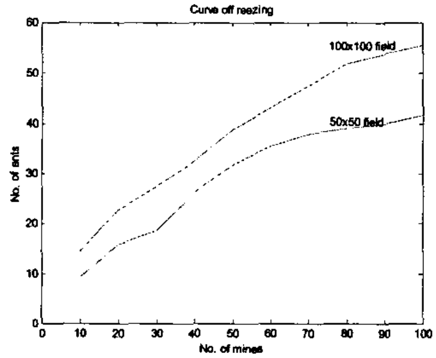

Fig. 5. Curve of freezing

The plot shows the dependence of the freezing curve on the field size and the number of mines present. The observable trend is that the rate of change of the freezing curve decreases with the increase in number of mines.

VI. 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 thea nts uset he information of them ines that it has detected in deciding on the future foraging strategy. Improved results can be obtained ift he ants adaptively change their map (the division of the foraging region into distinguishable regions) of the foraging area in accordance with the updated mine distribution. By updated mine distribution we mean the distribution that an ant would have after it has defused a mine at a particular point, in comparison to the initial mine distribution that it had assumed. Also the algorithm could be applied to scenariosw here 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.

VII. CONCLUSIONS

The paperd etails a swarm intelligence based approach to the problem of mine detection and the results obtained from simulations using different foraging strategies. The problem of mine detection is still solved using very traditional techniques. In our approach the use of swarm intelligence helps in creating a confidence for thed eployment of ant like robotic agents for the problem of mine detection. Our simulation results show thati n almost all cases the convergence is well assured. There can be situations where when the ratio of the number of minest o antsd eployed is low, then all the ants foraging may end themselves at the mines and wait for the others to arrive. Such a situation can be called *freezing*. Freezing, though considered negative is an observable feature. One solution to avoid the problem of freezing is to have a time bound for the ants to be in the waiting mode at a particular mine and henceforth resume their foraging.

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