Cooperative c-Marking Agents for the Foraging Problem

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***Abstract*— We consider the problem of foraging with multiple agents, in which agents must collect disseminate resources in an unknown and complex environment. So far, reactive multi-agent systems have been proposed, where agents can perform simultaneously exploration and path planning. In this work, we aim to decrease exploration and foraging time by increasing the level of cooperation between agents; to this end, we present in this paper a novel pheromone modeling in which pheromone's propagation and evaporation are managed by agents. As in c-marking agents, our agents are provided with very limited perceptions, and they can mark their environment. Simulation results demonstrate that the proposed model outperforms the c-marking agent-based systems in a foraging mission.**

Keywords- reactive agents; foraging task; digital pheromone; APF construction

I. INTRODUCTION

Foraging is a task that lends to multi-robots systems that can beat single robot systems in such a task. On the other side, the possible profit of multi-robots systems is conditioned by the level of cooperation [2]. Swarm intelligence is the study of collective complex and intelligent behaviors observed in natural systems where global swarm behaviors emerge as a result of local interactions between agents and global interactions between agents and environment [3]. Foraging is, therefore, a benchmark problem within swarm robotics [4]. A particularly interesting situation problem is when foraging robots have no a priori information about the locations of objects in unknown and complex environment. As wider searching spaces need more scalable and reliable solutions, distributed cooperative multi-robots systems are much adopted to achieve foraging missions.

Synthetic pheromones are one of the most popular swarm techniques that provide interesting solutions to problems such foraging [5]; most of these solutions create local minima that can lead the multi-robots system to fail. In [1], a pheromone is modeled as a static piece dropped and picked up by agents. The cooperation between agents is managed with the c-marking agents' algorithm. The pheromone has no propagation properties, that is minimizing the level of cooperation between agents. This hypothesis is very promising to achieve rapidly tasks such as foraging [6].

This paper presents a novel pheromone modeling that aims at increasing the level of cooperation between agents to achieve rapidly the foraging task. To this end, we present in this paper, a new behavioral model and an extension version of the c-marking agents' algorithm. This new behavioral model handles specific situations such as the presence of two resources in neighboring cells. Through simulation tests, the system is compared with the original one [1] in terms of the number of iterations required for achieving the foraging task.

The rest of paper is organized as follows. In Section 2, we discuss related works. A new pheromone modeling, behavioral model and extended algorithm (cooperative c-marking agent algorithm) are given in Section 3. Section 4 describes the simulation environment and an experimental comparison between the original c-marking and c-marking enhanced algorithm. Section 5 concludes our research.

II. RELATED WORK (PHEROMONE BASED TECHNIQUES FOR FORAGING)

Foraging is a benchmark problem for robotics, especially for multi robot systems [2]. It is the act of searching for any objects and collecting them at a storage point which is called base. Ostergaard et al. define it as "a two-step repetitive process in which (1) robots search a designated region of space for certain objects, and (2) once found these objects are brought to a goal region using some form of navigation" [7].

A wide range of approaches has been adopted to suggest solutions to the foraging problem in unknown environments. Most of them focus on examples of multi-robot foraging from within the field of swarm robotics. Three strategies for cooperation very known in this field are: information sharing [8], physical cooperation, which can be a cooperative grabbing [9][10], or a cooperative transport [11][12][13]. In multi-robot foraging it is well know that overall performance does not increase with increasing team size [14][15][16], division of labor in ant colonies has been well studied and there was a proposition of threshold model [17][18], some other works concentrate on individual adaptation and division of labor in ants that allow a swarm of robots to self-organize [19][20][21]. Pheromone based techniques inspired from ants are used for foraging with robots [22][23][24], where agents drop a quantity of pheromones in their environment in order to build gradients from sources to the

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base. This approach has some drawbacks, such as the computation of propagation and evaporation dynamics, and each agent needs specific mechanisms or materials that allow him to get back home. Panait and Luke [5] and Resnick [24] propose the use of a second pheromone diffusion from the base in order to avoid this last problem. In the same time, this solution can create new local minima.

An original approach has been proposed in [1] that allows agents to build optimal paths for foraging using only reactive agents, which have limited information about their environment. To keep track of the sources found and to build trails between sources and the base, agents drop a quantity of pheromones in their environment.

In this paper, we present a novel extension of the c-marking agents' algorithm, in order to increase the level of cooperation between agents.

III. COOPERATIVE C-MARKING AGENTS

The proposed multi agents system has the same properties of agents defined in [1]; the system is defined as a set of objects, which are static obstacles, sources and other agents, sources have fixed positions and agents are moving in the environment to achieve their own task:

A. *The pheromone model*

Two kinds of the pheromone's model are used in most of the works cited above. The first one integrates the management of the two modules propagation and evaporation in the pheromone, which is a complex task that causes in some cases building of local minima, the second one use the pheromone as a piece that does not propagate in the environment, and that can be picked up by agents when all is finished.

The proposed pheromones' model combines between the two properties cited before, thus the pheromone is considered as a piece that can be dropped and picked up by the agent, it has propagation and evaporation properties that are managed by the agent. The agent will creates a maximal trail (deposits a diffusible pheromone), if the quantity of resources is important for more attraction and recruitment of agents to the trails. If the quantity of resources is (or becomes) less than a fixed minimum quantity; the agent creates a minimal trail (deposits a non-diffusible pheromone) to avoid the attraction of other agents. This new modeling is shown by figure 1.

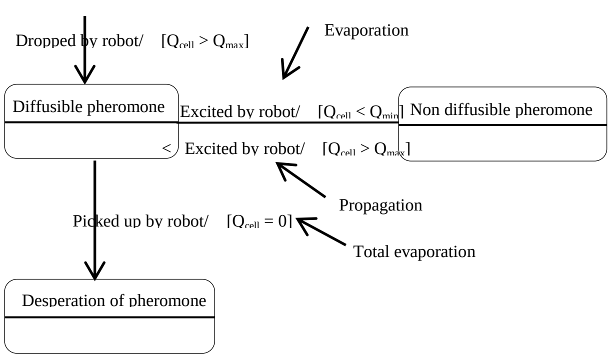

Figure 1. Pheromone modeling

The fact that the pheromone is managed by the agents (dropped, picked, propagated and evaporated); there will be no doubt that a non-operational trails steel existing between the base and an exhausted source.

B. *The environment model*

The environment is modeled as a squared grid with variable size that have resources in multiple locations, these locations are scattered randomly, and they are unknown by the agents; each location has a given quantity of resources. Cells in the environment can:

- Be an obstacle (grey color);
- Contain a resource (green color) with a limited quantity Q max
- Be the base (red color), positioned in all simulations in the environment's center, and form the start point of all the agents;
- Contain an agent

C. *The agent model*

Agents have limited information about their environment; they occupy a cell, and each agent can:

- Move from a cell to another, which is not an obstacle in the four direction;
- Read and write values in the current cell;
- Perceive and read the values of the four neighboring cells, so he can detect resources, and he can load a quantity of resources according to Qte_{max}.

Increasing the level of cooperation between agents, and dealing with specific situations such as the two resource neighboring cells, can decrease dramatically the time of foraging. To achieve those goals, we address the new agent's behavior given by Figure 2 (Cooperative c-marking agents) and the enhanced algorithm corresponding to cooperative c-marking agents is given by the algorithm (extension of the c-marking agents) bellow:

Algorithm 1: Cooperative c-marking agents

SEARCH & CLIMB *(Simonin & al, 2010)*

If a resource is detected in a neighboring cell THEN
    move into that cell and execute LOADING
ELSE IF neighboring cells are colored and different from the previous position THEN move to highest-valued such cell,
ELSE execute EXPLORATION & APF CONSTRUCTION

LOADING

Pick up a quantity Qte_{max} of resource ;
IF the cell is not exhausted of resources THEN
  IF $Q_{cell} >= Q_{max}$ THEN
    IF the cell is colored THEN execute RETURN TO BASE
    ELSE execute RETURN & COLOR MAX TRAIL
  ELSE IF $Q_{cell} = Q_{min}$ THEN
      IF the cell is colored THEN execute RETURN & ERASE MAX TRAIL
      ELSE execute RETURN & MIN TRAIL
  ELSE IF $Q_{cell} < Q_{min}$ THEN
    IF the cell is colored THEN execute RETURN TO

(1)

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BASE
ELSE execute RETURN & COLOR MIN TRAIL

ELSE IF the cell is exhausted THEN
IF (resource found in neighboring cells) and (exist trail) THEN
Color current cell with trail color
IF $Q_{cell} >= Q_{max}$ THEN color the 4 neighboring cells with light gray color and execute RETURN TO BASE
ELSE IF $Q_{cell} <= Q_{min}$ THEN execute RETURN TO BASE
ELSE IF (resource found in neighboring cells) and (not exist trail) THEN execute ***(1)***
ELSE IF the cell is colored THEN execute RETURN & ERASE MIN TRAIL
ELSE execute RETURN TO BASE **;**

RETURN & COLOR MAX TRAIL
IF the base is reached THEN
unload resource and execute SEARCH & CLIMB
ELSE move to a new neighboring cell with the least value
Color the current cell in a trail color -dark gray color- (it will be propagates to the 4 neighboring cells with another color trail –light gray color-);

RETURN & COLOR MIN TRAIL *(Simonin & al, 2010)*
IF the base is reached THEN
unload resource and execute SEACH & CLIMB
ELSE move to a new neighboring cell with the least value
Color the that cell in a trail color;

RETURN & ERASE MAX TRAIL
IF the agent is located at base THEN UNLOAD resource & execute SEARCH & CLIMB
ELSE Move to a neighboring colored cell with the least value
Erase the color of the 4 neighboring cells to the default color;

RETURN & ERASE MIN TRAIL
IF the base is reached THEN UNLOAD resource & execute SEARCH & CLIMB
ELSE IF the number of colored neighboring cells >=2 THEN execute RETURN TO BASE
Else IF there is a colored cell with least value THEN
move to it & erase the color to the default one.

RETURN TO BASE
If the base is reached THEN UNLOAD resource and execute SEARCH & CLIMB
ELSE IF there is a neighboring colored cell with min value THEN move to it and UPDATE VALUE
ELSE move to a cell with min value & UPDATE VALUE

In the foraging system shown in Figure 2, each robot search resource in a pseudo random walk, and then it brings the discovered resources to the base. In its way, the robot creates paths to keep track of resources found, and to attract more robots to the discovered resource cell. Paths are of two kinds; max trails, which are formed by a diffusible digital pheromones (i.e. these are larger paths, and they are diffusible to the four neighboring cells), and min trails, which are formed by a non-diffusible pheromones. The robot follows the following rules according to the quantity of resources:

- If the quantity of resources is greater than a quantity max and there is no trail the robot drops diffusible pheromones (creation of max trails), else he climbs the existing trail;
- If the quantity is equal to a quantity min and there is a trail then the agent will climb it and erase the max trail to avoid the attraction of other robots, else if there is no trail, the robot will return and color min trail;
- If the quantity is less than a quantity min, and there is a trail then the robot climbs it else it creates a min trail.
- If the base is reached, the robot unloads resources and chooses between climb an existing trail and searching for a resource.

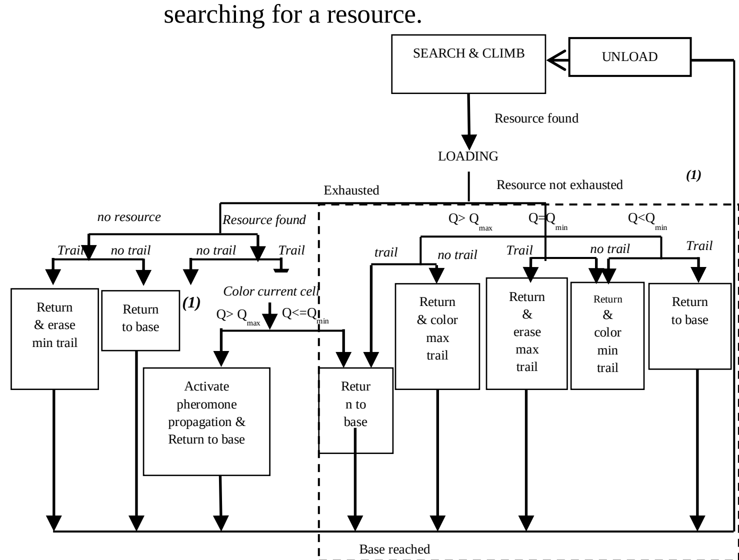

Figure 2. Cooperative c-marking agent behavior

IV. SIMULATION RESULTS AND COMPARAISON

According to the simulation results, we compared the proposed system with the original foraging system for verifying its effectiveness. The c-marking agent system offers a small level of cooperation between agents, whereas the ameliorated system offers a great level of cooperation, which decreases the foraging time.

We tested with square environments (grid with variable size); obstacles and resource locations are disseminated randomly in the environment, and all the agents start from the center (base). Several setups were used to test the model:

Setup 1 is defined as follows:

- An environment with 40 X 40 cells, 30% obstacles and 20 cells are resource locations; each resource contains 1000 units of resources.
- Each agent can load a maximum of 100 units.

As in [1], we define time as the number of iteration required to discover and exhaust all the resources in the environment. We evaluate the performance of the two models in different configurations (number of agents, size of the environment).

A. *Influence of the number of agents on performance*

Using the setup 1, and varying the number of agents from 5 to 160 agents, we obtained the results illustrated by Figure 3 and Table 1. Experiments show that increasing the number of agents decreases the time of foraging. This is due to the great level of cooperation.

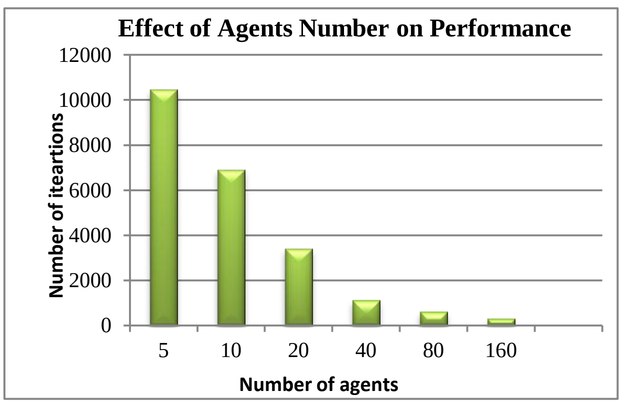

Figure3. Performance of Cooperative c-marking agents in setup 1

TABLE 1 INFLUENCE OF NUMBER OF AGENTS ON THE PERFORMANCE OF COOPERATIVE C-MARKING AGENTS

Number of agents	5	10	20	40	80
Iteration number	10476	6917	3403	1125	609

B. *Influence of the environment size on performance*

In this case, the number of agents is fixed and the environment size is variable. We used the setup 2 to see how the size of the environment affects the performance of the proposed model.

Setup 2 is defined by:

- Environments contain 5% obstacle density and 20 cells are resource locations; each resource contains 2000 units of resources.
- The number of agents is 50. Each agent can transport a maximum of 100 units.

Table 2 and Figure 4 show the performance of the algorithm for environments of varying sizes ranging from 12x12 to 100x100.

The results show that the foraging time decreases with increasing the size of the environment. The solution becomes ineffective due to the increase in exploration time. The problem of dead connected trails creates local minima that can lead to freeze a great number of agents in the local minima vicinity.

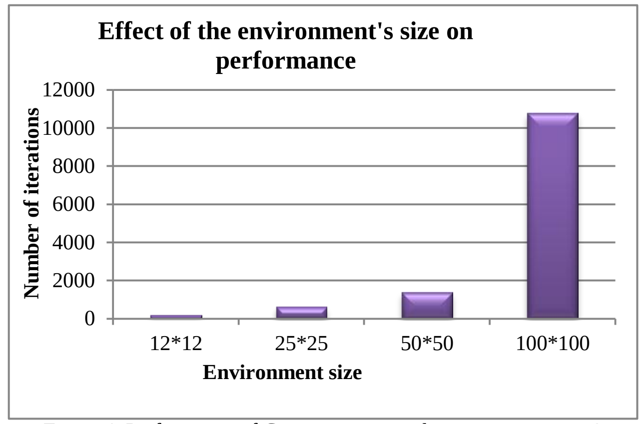

Figure 4. Performance of Cooperative c-marking agents in setup2

TABLE 2 INFLUENCE OF THE ENVIRONMENT SIZE ON THE PERFORMANCE OF COOPERATIVE C-MARKING AGENTS

Environment size	12*12	25*25	50*50	100*100
Iteration number	*192*	652	1395	10777

C. *Influence of the obstacles on performance*

Obstacles are disseminated in a random way in the environment. Such situation allows us to test the robustness of the algorithm to obstacles.

Setup 3 is defined by:

- Environment size is 41 X 41 cells, 20 cells are resource locations; each resource contains 1000 units of resources;
- Number of agents is 10 and each one can transport a maximum of 100 units;

The obstacle percentage is varying from 15 to 30 % of the environment surface. Results are shown in Table 3 and in Figure 5, which demonstrate that the performances do not depend on the density of obstacles. The algorithm offers an interesting level of robustness to obstacles.

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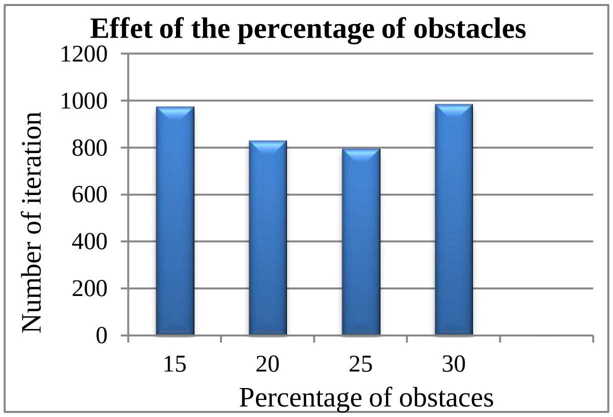

Figure 5. Performance of Cooperative c-marking agents in setup3

TABLE 3 INFLUENCE OF THE PERCENTAGE OF OBSTACLES ON THE PERFORMANCE OF COOPERATIVE C-MARKING AGENTS

Percentage of obstacles	15	20	25	30
Iteration number	976	831	796	985

D. *Comparaison with c-marking agents model*

Simulating the ant model requires more environment management mechanisms in which propagation of the pheromones represents a high computational cost. The main advantage of marking agents is their abilities of creating quick paths to the base during the exploration phase [1]. In the proposed model, the first problem is avoided by giving a new modeling for the digital pheromone, and the local minima problem is also avoided. Due to this last, agents are able to go back home easily.

Figure 6 presents a comparison between the two models. It shows that the proposed model gives more efficiency in time than the c-marking agents in case of varying the number of agents. This is due specifically to the great level of cooperation which decreases the exploration time. Figure 7 gives a comparison between the two models by varying the environment's size. Results show that this model gives a less efficiency in time than the c-marking agents' model. We think that this ineffectiveness of results is due to a problem that appears during the simulations, there is a possibility that two or more trail are connected (have common cells in some part of the trail); or crossed ones, when the agent in trail 1 exhaust the resource, it will erase the trail and this will cause the erase of the common portion of trail; the agents in the other trail have no way to continue to the base, or to the resource, because they look for colored cells , with this phenomena a great number of agents will be trapped and the simulation is continued with just those agents which are not trapped and this will increase the number of iteration .

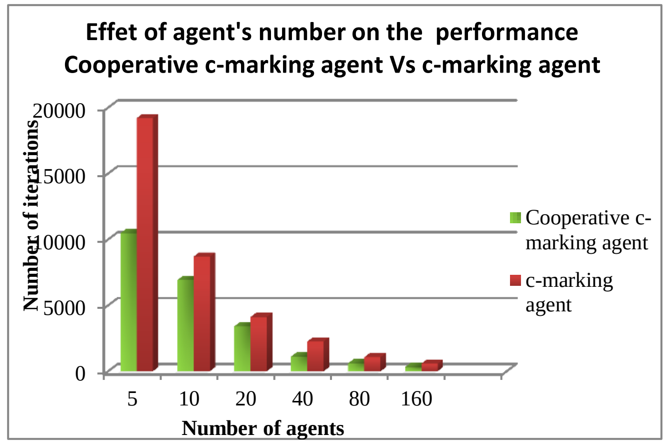

Figure 6. Effect of the number of agents
Cooperative c-marking agents Vs c-marking agents

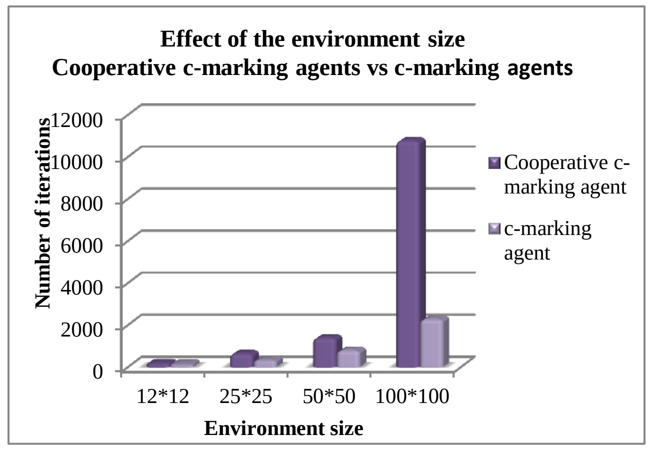

Figure 7. Effect of the environment size
Cooperative c-marking agents Vs c-marking agents

V. CONCLUSION AND FUTURE WORK

A multi agent model simulation and a new version of the c-marking agents' algorithm to increase the cooperation between agents and to decrease the time of foraging have been presented. Some other problems such as neighboring resources is solved with our new model and results indicates that the use of the new pheromone modeling give more efficiency in time than the original one. In perspective, we think that robot's behavior can be enhanced by introducing both new exploration approaches and solutions to problems such as trail erasing and APF fast convergence.

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