Collaborative Foraging Using a new Pheromone and Behavioral Model

ZEDADRA Ouarda
LabSTIC Laboratory, 8 may 1945 University, BP 401 Guelma, Algeria
Department of computer science, Badji Mokhtar University, BP 12, Annaba, Algeria
Zedadra_nawel1@yahoo.fr

Nicolas JOUANDEAU
Advanced Computing laboratory of saint-Denis (LIASD)
Paris 8 University, Saint Denis 93526, France
Email: n@ai.univ-paris8.fr

SERIDI Hamid
LabSTIC Laboratory, 8 may 1945 University, BP 401 Guelma, Algeria
seridihamid@yahoo.fr

***Abstract*— we consider the problem of foraging with multiple agents, in which agents must collect disseminate resources in an unknown and complex environment. An efficient foraging should benefit from the presence of multiple agents, where cooperation between agents is a key issue for improvements. To do so, we propose a new distributed foraging mechanism. The aim is to adopt a new behavioral model regarding sources' affluence and pheromone's management. Simulations are done by considering agents as autonomous robots with goods transportation capacity, up to swarms that consist of 160 robots. Results demonstrate that the proposed model gives better results than c-marking agent model.**

Keywords—Collaborative foraging;reactive agents;digital pheromone;behavioral model.

I. INTRODUCTION

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 [1]. Foraging is a task that lends to multi-robot systems [2], that is therefore, a benchmark problem within swarm robotics [3]. A particularly interesting situation problem is when foraging robots have no priory information about the environment. Distributed cooperative multi-robot systems are much adopted to achieve foraging missions in such cases, but communication mechanisms are needed for coordination. One of the indirect communication mechanisms used for multi-agent coordination in shared environment is the pheromone deposits [4]. This approach is inspired by the study of the stigmergy process conducted on self-organized societies of insects [5]. The foraging behavior of ants is an example of stigmergy where ants drop pheromones as they move in the environment. Ants' navigation is stimulated through local observations of pheromone's strength that produces a gradient by evaporation. The global behavior emerges from these simple local interactions. The scalability potential of such approach makes it an interesting solution to many problems that are similar to foraging [6]. Most of studies in both artificial life and robotics carried out on synthetic pheromones and use a large vocabularies linked to pheromone, coming from propagation and evaporation properties [7] [8]. These properties allow a group of agents to adapt to situations dynamically, even with static pheromone like in [9].

The main goal of our work is to increase the cooperation between robots when the quantity of resources is more important and to decrease the cooperation when the quantity is less important. To this end, we propose the new foraging model by means of resource quantity and pheromone's management. In other words, robots regarding the affluence of resource in locations decide to deposit diffusible or non-diffusible pheromone to attract more or less number of other robots. Through simulation tests, the system is compared with the original one [9] in terms of the number of iterations that are required to achieve the foraging task.

The rest of paper is organized as follows. In Section 2, we discuss related works. New pheromone and behavioral models, agent and environment models are given in Section 3, also a finite state machine for collective foraging is given in section 4. Section 5 describes the simulation results and an experimental comparison between the original c-marking agents model and our new model. Section 6 concludes.

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 to a storage point which is called base. Ostergaard and al [10] define it as ' 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 '. 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. The three main strategies for cooperation in this field are: information sharing [11], physical cooperation [12] [13] [14] [15] [16], and division of labor [17] [18] [19] [20] [21] [22] [23] [24]. Pheromone based techniques inspired from ants are useful for foraging with multiple robots [25] [26]. 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 [6] and [8] 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 minimum.

An original approach has been proposed in [9] that allow reactive agents to build optimal paths for foraging, which have limited information about their environment. To keep track of found resources locations and to build trails between them and the base, agents drop a quantity of pheromones inside their environment. In this paper, we present a new behavioral model for collective foraging robots inspired from the c-marking agents one, based on resources' affluence and on a new pheromone model.

III. Modeling System Components (Pheromone, Environment and Robots)

The different components of our reactive multi-agent system are given as follows:

A. *Pheromone Model*

Figure 1 shows the model of the pheromone like it is proposed in our previous works [27].

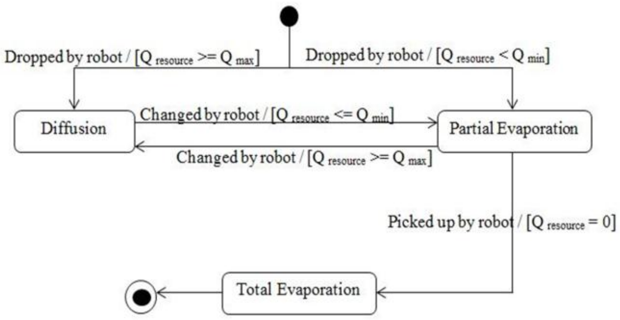

Fig. 1. State diagram of our digital pheromone

The pheromone is modeled as a piece that has diffusible and evaporation properties, these are managed by the robot and not the environment, it is always in one of the three states: diffusion, partial evaporation or total evaporation. The initial state is either diffusion or partial evaporation regarding the resources quantity Q_{res}. If the quantity is less or equal to a minimal quantity of resources Q_{min}, the pheromone takes the partial evaporation state (it takes place just in current cell), else the pheromone takes the diffusion state. There is a transition from diffusion to partial evaporation (and vise versa) when the quantity of objects becomes less than Q_{min} (more than a Q_{max}) and a transition from partial evaporation to total evaporation when the quantity of objects is equal to 0. Total evaporation state is the final state in the pheromone's life cycle. All those transitions are managed by robots which results in attracting more robots to the trails, with no worries of local minimum problems. By achieving this goal we increase the cooperation between agents and by the way the foraging time decreases.

B. *Environment Model*

The environment is modeled as a squared grid with variable size that has resources in multiple locations. These locations are scattered randomly and are unknown by the robots. 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;
- Be the base (red color), positioned in all simulations in the environment's center and form the starting point of all the robots;
- Contain a robot (blue color).

C. Robot Model

Agents have limited information about their environment. Due to the pheromone model, agents manipulate real pieces and are then close to real robots. At each time step, each robot can:

- Move from a cell to another, which is not an obstacle in the four cardinal directions;
- Read and write values in the current cell;
- Perceive and read the values of the four neighboring cells. So robots can detect and load resources according to a maximum capacity QTE_{max}.

IV. Finite State Machine for Collective Foraging

Figure 2 shows the Finite State Machine of an autonomous foraging robot which is an enhanced version of the c-marking agents model [9]. A robot in its life cycle goes through the following states: 'search and climb', 'loading', 'return and drop pheromone'. This last pheromone interaction state can also be one of the four sub-states~: 'return and color max trail', 'return to base', 'return and color min trail' or 'return and remove max trail'; 'return and pick up', which can be one of the four sub-states: 'return and remove min trail', 'return to base', 'return and drop' or 'return and color max trail'. In all cases when the base is reached, robot executes the state unload and changes automatically when finished to the search and climb state. The enhanced algorithm corresponding to cooperative c-marking agents V1 is given in Algorithm 1:

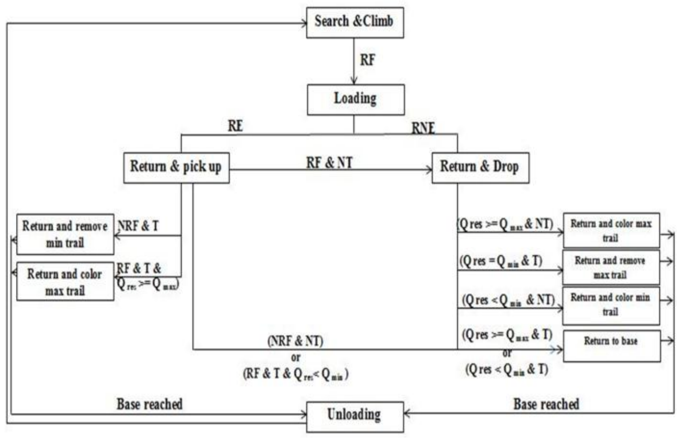

Fig. 2. State diagram of our digital pheromone

Transitions:RF: Resource Found, RNE: Resource Not Exhausted, RE: Resource Exhausted, NT: No Trail exists, T: Trail exists, NRF : No Resource found, Q_{res}: quantity of resources, Q_{max}: quantity maximum of resources, Q_{min}: quantity minimal of resources

Algorithm 1: Cooperative c-marking agentsV1

SEARCH and CLIMB (same as [9])

LOADING
Pick up a quantity QTE $_{max}$
IF (the cell is not exhausted of resources) **Then** *RETURN AND DROP*
ELSE execute *RETURN AND PICK UP*

RETURN AND DROP
IF ($Q_{res} >= Q_{max}$ and no trail exists) **Then** execute *RETURN AND COLOR MAX TRAIL*
ELSIF ($Q_{res} = Q_{min}$ and trail exists) **Then** execute *RETURN AND REMOVE MAX TRAIL*
ELSIF ($Q_{res} < Q_{min}$ and no trail exists) Then *RETURN AND COLOR MIN TRAIL*
ELSIF ($Q_{res} >= Q_{max}$ and trail exists or $Q_{res} < Q_{min}$ and a trail exists) Then *RETURN TO BASE*

RETURN AND PICK UP
IF (a resource is found in a neighboring cell and no trail exists) **Then** execute *RETURN AND DROP*
ELSIF (no resource found and trail exists) **Then** execute *REMOVE MIN TRAIL*
ELSIF (resource found and no trail exists or a resource found and $Q_{res} < Q_{min}$) **Then** execute *RETURN TO BASE*

RETURN AND COLOR MAX TRAIL
IF (base is reached) **Then** Unload resources and execute *SEARCH AND CLIMB*
ELSE

- Move to a new neighboring, not colored cell with the least value;
- Color the current cell with dark gray value, and the 4 neighboring cells with light gray color

RETURN AND COLOR MIN TRAIL
IF (base is reached) **Then** unload resources and execute *SEARCH AND CLIMB*
ELSE

- Move to a new neighboring, not colored cell with the least value;
- Color the current cell with dark gray color

RETURN AND REMOVE MAX TRAIL (same as [27])

RETURN AND REMOVE MIN TRAIL (same as [27])

RETURN TO BASE (same as [9])

V. SIMULATION RESULTS AND COMPARISON

To explore the collective foraging behavior of a robotic swarm, we have used two setups (setup1, setup2), in the first one we change the number of robots from 5 to 160, and in the second we change the environment's size from 12X12 to 100X100. results shown in our previous work [27] give interesting results regarding setup1, but less interesting ones regarding setup2, because a large number of robots get stuck in the not removed portions of trails, which increases the foraging time, to deal with this problem the behavior of our autonomous foraging robots have been improved in this work, it is given in details in the two behaviors (RETURN AND COLOR MAX TRAIL and RETURN AND COLOR MIN TRAIL)

Setup 1:

- Environments are 40 X 40 cells large with 30% obstacles; 20 cells are resources' locations; each resource contains
- 1000 units of resources;
- Each robot can load a maximum of 100 units.

Setup 2:

- Environments contain 5% obstacles; 20 cells are resources' locations; each resource contains 2000 units of resources;
- The number of robots is 50. Each robot can carry a maximum of 100 units.

We define time as the number of iterations required discovering and exhausting all the resources in the environment, as in [9]. Figure 3 and table I show the simulation results of setup2 that tests the influence of environment's size on system performance.

Using setup 2 and varying the size of the environment from 12X12 to 100X100 cells. We got the results shown in Fig. 3 and in table I. Results show that the foraging time increases in a less manner by increasing the size of the environment, until 100X100 we observe a great increase in the foraging time. We compared the proposed behavioral model to the c-marking agents one [9]. Two kinds of comparisons were done, the first one is about the influence of the number of robots on system performance, where the proposed model gives more efficiency in time than the c-marking one [27]. The second one is about the influence of the environment's size on system performance (Figure 4), simulations show that the enhancement in the two behaviors RETURN AND COLOR MAX TRAIL AND RETURN AND COLOR MIN TRAIL gives interesting results among the c-marking agents model.

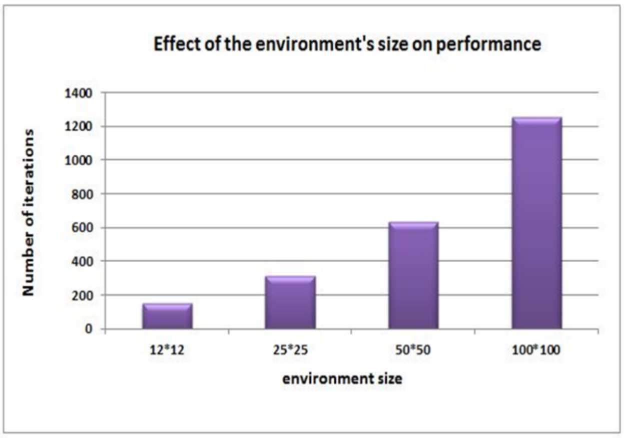

Fig. 3. Simulation results according to setup2

TABLE I. EFFECT OF ENVIRONMENT'S SIZE ON PERFORMANCE

Environment's size	12X12	25X25	50X50	100X100
Number of iterations	150	315	630	1250

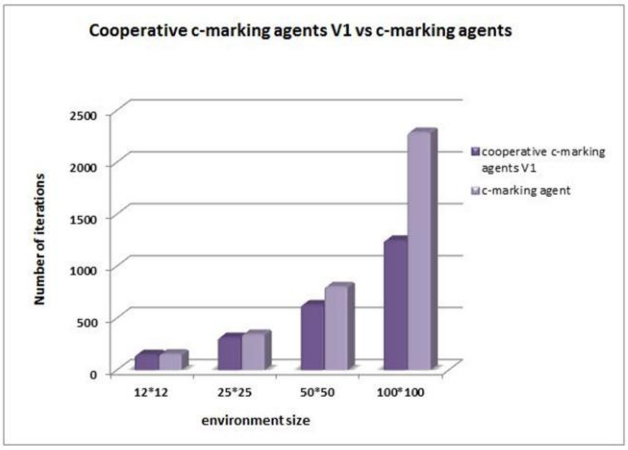

Fig. 4. Results comparsion with c-marking agents model

We run in the next example 10 cooperative c-marking agents V1, which start all from the base.

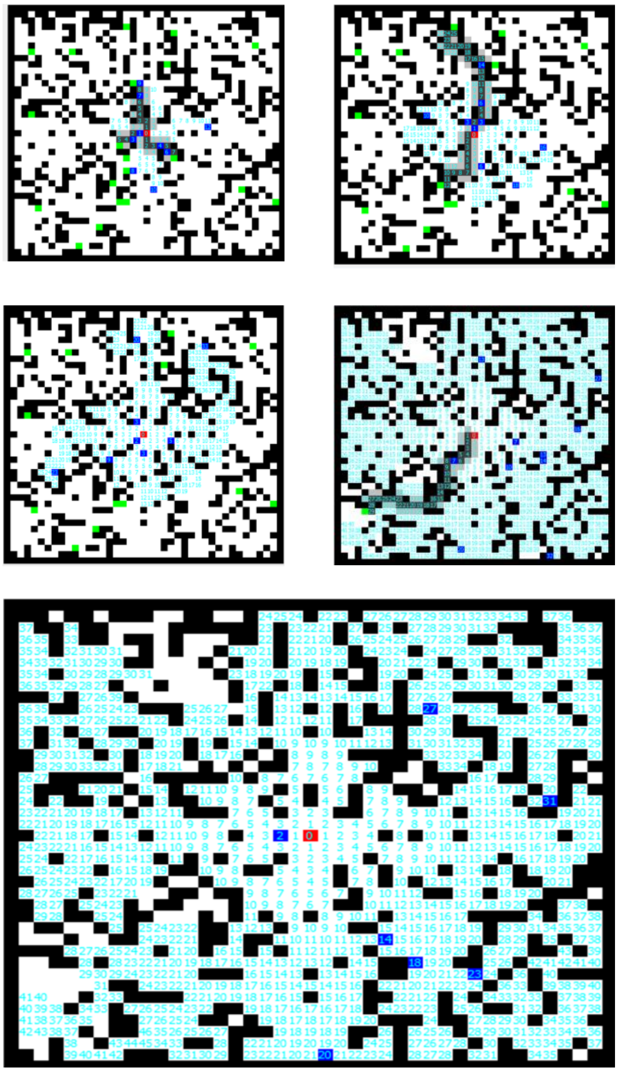

Fig. 5. Snapshots at steps 24, 186, 344, 1765 and 1780

We observe in Figure 5 at step 24, the construction of the Numerical Potential Field (APF) starts out as a pseudo-circular front computation, we can also observe that 3 resource locations were discovered and 7 agents are involved in transport of resources along 3 trails make by others (min trails are the black ones, and max trails are those with the gray color, this gray color represents the diffusion of the pheromone). Figure 5 at step 186 shows a discover of two other resource locations, whereas the three last ones are totally exhausted. Figure 5 at step 344 shows the 10 agents in a search behavior where no resource location is discovered yet. Figure 5 at step 1765 shows a situation where all resource locations are discovered and exhausted unless one which is under exploitation by two agents and the other agents execute a search behavior. Around 1780 iteration, all resource locations have been discovered and exhausted.

VI. CONCLUSION AND FUTURE WORK

Based on the new digital pheromone model, we proposed in this paper a new behavioral model that aims to decrease the foraging time regarding to a new pheromone model and regarding the quantity of resources in all locations. Simulations give interesting results among an original model regarding to the number of robots depending on the environment's size. In perspective, we think that robot's behavior can be enhanced by introducing both new exploration approaches and solutions to problems such as APF fast convergence.

REFERENCES

[1] E. Bonabeau, M. Dorigo, and G. Theraulaz, “Swarm intelligence- from natural to artificial systems”. Oxford University Press, 1999.

[2] A. Winfield, “Foraging robots”. Encyclopedia of Complexity and Systems Science. Springer, pages 3682-3700, 2009.

[3] M. Dorigo and M. Birattari, “Swarm intelligence”. Scholarpedia, 2007.

[4] B. Hrolenok, S. Luke, K. Sullivan, and C. Vo. “Collaborative foraging using beacons”. In AAMAS'10. IFAAMAS, pages 1197-1204, 2010.

[5] E. Bounabeau and G. Theraulaz, “Intelligence Collective”. Hermes edition, 1994.

[6] L. Panait and S. Luke, “A pheromone-based utility model for collaborative foraging”. In AAMAS'04. ACM, pages 36-43, 2004.

[7] M. Nakamura and K. Kurumatani. “Formation mechanism of pheromone pattern and control of foraging behavior in an ant colony model”, 1997.

[8] M. Resnick, “Turtles, termites, and traffic jams: Explorations in massively parallel microworlds”. Cambridge, MIT Press, 1994.

[9] O. Simonin, F. Charpillet, and E. Thierry, “Collective construction of numerical potential fields for the foraging problem”. Technical report, INRIA, France, 2007.

[10] E. H. Ostergaard, G. S. Sukhatme, and M. J. Mataric. “Emergent bucket brigading: A simple mechanism for improving performance in multi robot constrained-space foraging tasks”. In Int. Conf. On Autonomous Agents, 2001.

[11] M. J. Mataric and M. J. Marjanovic. “Synthesizing complex behaviors by composing simple primitives”. In Self-Organization and Life, From Simple Rules to Global Complexity, European Conference on Artificial Life (ECAL-93)}, pages 698-707, 1993.

[12] A. J. Ijspeert, A. Martinoli, A. Billard, and L. M. Gambardella. “Collaboration through the exploration of local interactions in autonomous collective robotics: The stick pulling experiment. Autonoumous robots”, 2001.

[13] K. Easton A. Martinoli and W. Agassounon. “Modeling swarm robotic systems: A case study in collaborative distributed manipulation”. Journal of Robotics research, Special Issue on Experimental Robotics, 2004.

[14] L. E. Paker, “Alliance: an architecture for fault tolerant, cooperative control of heterogeneous mobile robots”, In IEEE/ RSJ International Conference on Intelligent Robots and Systems, 1994.

[15] R. Grob, E. Tuci, M. Dorigo, M. Bonani, and F. Mondada, “Object transport by modular robots that self-assemble”. In IEEE International Conference on Robotics and Automation, 2006.

[16] M. Dorigo, E.Tuci, R.Grob, V.Trianni, T.H. Labella, S.Nouyan, and C. Ampatzis, “The swarm-bot project”. In Swarm Robotics Workshop: State-of-the-art survey, number 3342 in Lecture Notes in Computer Science, Berlin Heidelberg, Springer Verlag, 2005.

[17] T. Balch and R. C. Arkin, “Communication in reactive multiagent robotic systems”. Autonomous robots, 1994.

[18] D. Goldberg and M. J. Mataric, “Interference as a tool for designing and evaluating multi robot controllers”. In 14th National Conference on Artificial intelligence (AAAI-97). MIT Press, 1997.

[19] K. Lerman, “Mathematical model of foraging in a group of robots inspired by ants foraging behavior”. In ACM Transactions on Autonomous and Adaptive Systems, 2006.

[20] E. Bonabeau, C. Theraulaz, and J. L. Deneubourg, “Quantitative study of the fixed threshold model for the regulation of division of labor in insect societies”. In the RoyalSociety of London, Series B Biological Sciences, 1996.

[21] E. Bonabeau, G. Theraulaz, and J.L. Deneubourg, “Fixed response thresholds and the regulation of division of labour in insect societies”. In Bulletin of Mathematical Biology, 1998.

[22] M. Krieger and J.B. Billeter, “The call of duty: Self-organised task allocation in a population of up to twelve mobile robots”. In Jour of Robotics and Autonomous Systems, 2000.

[23] J. L. Deneubourg, S. Goss, J. M. Pasteels, D. Fresneau, and J. P. Lachaud, “Self-organization mechanisms in ant societies (ii): learning in foraging and division of labour”. Experientia Suppl, 1987.

[24] T. H. Labella, M. Dorigo, and J. L. Deneubourg, “Division of labour in a group of robots inspired by ants foraging behaviour”. ACM Transactions on Autonomous and Adaptive Systems, 2006.

[25] J. L. Deneubourg, S. Aron, S. Goss, J. M. Pasteels, and G. Duerrinck, “Random behavior, amplification processes and number of participants: How they contribute to the foraging properties of ants”. Physica, 1986.

[26] B. Holldobler and E.Wilson, “The Ants”. 1990.

[27] O. Zedadra, N. Jouandeau, H.Seridi, “Cooperative c-marking agents for the foraging problem”. In the Fourth International Conference on Advances in System Simulation, IARIA, 2012.