Inverted Ant Colony Optimization for Search and Rescue in an Unknown Maze-like Indoor Environment

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ABSTRACT

We demonstrate the applicability of inverted Ant Colony Optimization (iACO) for target search in a complex unknown indoor environment simulated by a maze. The colony of autonomous ants lay repellent pheromones to speed up exploration of the unknown maze instead of reinforcing presence in already visited areas. The role of a target-collocated beacon signal within the maze is evaluated in terms of its utility to guide the search. Variants of iACO were developed, with beacon initialization (iACO-B), and with increased sensing ranges (iACO-R with a 2-step far-sightedness) to quantify the most effective one. The presented models can be implemented with self-organizing wireless sensor networks carried by autonomous drones or vehicles and can offer life-saving services of localizing victims of natural disasters or during major infrastructure failures.

CCS CONCEPTS

•**Computing methodologies** → *Planning under uncertainty; Multi-agent planning; Discrete space search; Intelligent agents;*

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1 INTRODUCTION

With Mobile Ad Hoc Networks becoming the core of the IT infrastructure, static communication topologies become extended, or even replaced by the mobile nodes of ad hoc networks where they can deployed as per the exact requirement, thereby reducing cost and energy expenditure in providing services [1][2]. Such setups become particularly attractive in situations and tasks where human lives might be at peril like for civilian defense, disaster relief and/or search and rescue (SAR) operations[3].

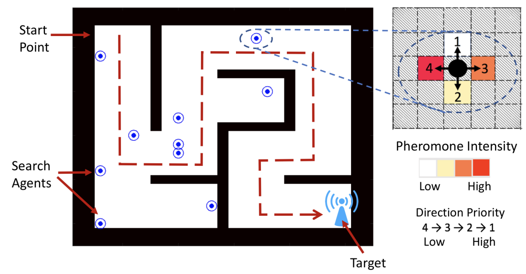

Figure 1: A SAR operation modeled as a maze solving problem. The SAR can be implemented as an adaption of ACO performed at each step in the maze where the decision making process is partially influenced by the level of deposited pheromones.

From an optimization point of view, the search for a victim in a randomized environment is modeled as a maze solving problem where search time can be reduced by optimizing the path taken to reach the target and the maze walls represent the random obstacles. Maze solving, in a known environment, using global path planning has been a widely attacked research problem over the years, with several main issues having been addressed [4][5][6], but maze solving in an unknown environment is an issue of local path planning. Taking inspiration from the innate local problem solving sense of swarms of animals and insects and following the work in [7],[8] and [9], we explore the use of Ant Colony Optimization (ACO), to develop a self-adaptive, evolutionary path strategy that will revolutionize applications for operation in critical, unknown environments like SAR. This paper answers the following questions in developing a local path planning strategy:

(1) The use of ACO in reducing the number of steps needed to solve a maze
(2) The influence of a beacon signal to guide the search
(3) How does the path planning strategy scale with the size and complexity of the search space

2 AGENT DECISION MAKING MODELS

The research problem is modeled as a maze solving problem guided by the strength of a beacon, co-located with the target, that is

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modeled using a modified ITU Indoor path loss model

$$PL[dB] = 20log_{10}(f) + 28log_{10}(d) - 28 + (w \times c) \quad (1)$$

where w = 4.4349 is the wall attenuation factor (for brick wall) [?], c is the wall count encountered, f = 2400 MHz is the frequency channel of communication for standard Wi-Fi, and d is the distance, in meters, from the beacon source [10].

In the maze, ants are limited to a 4-directional movement and the ACO probability density function is given by

$$P_i(t+1) = \frac{(c + n_i(t))^{\alpha}}{\sum_{i=1}^{4}(c + n_i(t))^{\alpha}} \quad (2)$$

where $P_i(t+1)$ is the probability of moving in direction i, $n_i(t)$ is the amount of pheromone in block i, c is the degree of attraction to an unexplored path, and α is the bias to using a pheromone concentrated path.

In pure ACO, ants were noticed to be clustering together, due to the attractive pull of pheromone which inhibits exploration. To counter this effect, an inverted ACO (iACO) model was developed, where the pheromone was designed to be repulsive. With promising initial results with iACO, 2 new versions of iACO: iACO with beacon initialization (iACO-B) and with increased sensing ranges (iACO-R) were developed. iACO-B initiates the search with pheromone levels proportional to the received beacon signal strength, adding an overall sense of direction in the agents. In iACO-R, ants have an increased sensing range which incorporates a slight far-sightedness in the ants' decision making. A general working of ACO-based models is summarized in Algorithm 1.

```
initialization;
possible moves = [stay, right, left, front, back];
while target not found do
    for each ant do
        Generate list of all possible next locations;
        Acquire pheromone information of all next locations;
        Roulette Wheel ← generate probabilities of moving to
          each next location;
        Spin Roulette Wheel to pick next location;
        Update current position and pheromone levels;
    end
end
```

Algorithm 1: iACO Ants' Decision Making Algorithm

3 RESULTS AND DISCUSSION

All 4 ACO based models were simulated 30 times each to average out the effect of the random nature of the heuristic. The performances of the 4 models are compared with a purely random movement solution, in terms of number of iterations needed to locate the target, which is the equivalent of solving the maze. All simulations are performed on a 2.6 GHz Intel Core i7 processor running a 2016a 64-bit version of MATLAB.

Figure 2 compares the performance of the 5 models when simulated with 100 ants each on the 3 different sample mazes. All 5 models vary almost linearly with a change in the size and complexity of the maze. The pure ACO based model did not seem to introduce much of an improvement, compared to a purely random

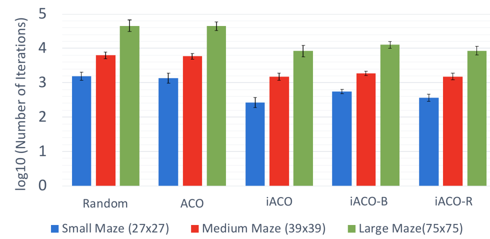

Figure 2: Comparing the performance of the 4 ACO based models and a random movement solution in solving the 3 different sized mazes with 100 ants each.

solution. This lack of improvement can be attributed to the clustering effect of pheromone in pure ACO that is likely limiting the exploration of the maze. iACO is the best performing algorithm among the 5, closely followed by iACO-R. Contrary to expectations, iACO with beacon initialization did not positively add to the performance due to a trapping effect noticed in the simulation, where ants get trapped in nooks of the maze while being pulled towards the target.

4 CONCLUSION & FUTURE WORK

Real time search on the maze in an unknown environment with a local path planning is addressed with variants of ACO, such as inverted ACO (iACO), iACO-R, and iACO-B, and tested with variable maze size and complexities. It is shown that iACO is is the quickest of all variants in solving the maze. More work needs to be done to improve the influence of beacon on the search.

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REFERENCES

[1] L. Mainetti, L. Patrono, and A. Vilei. Evolution of Wireless Sensor Networks towards the Internet of Things: A survey. In *Software, Telecommunications and Computer Networks (SoftCOM), 2011 19th International Conference on*, pages 1–6. IEEE, 2011.
[2] Y. Li and L. Cai. UAV-assisted dynamic coverage in a heterogeneous cellular system. *IEEE Network*, 31(4):56–61, 2017.
[3] Yugang Liu and Goldie Nejat. Robotic urban search and rescue: A survey from the control perspective. *Journal of Intelligent & Robotic Systems*, 72(2):147–165, 2013.
[4] S. Tjiharjadi and E. Setiawan. Design and implementation of a path finding robot using Flood Fill algorithm.
[5] G. Rivera. Path planning for general mazes. Master's thesis, Missouri University of Science and Technology, 2012.
[6] F. Bounini, D. Gingras, H. Pollart, and D. Gruyer. Modified Artificial Potential Field method for online path planning applications. In *Intelligent Vehicles Symposium (IV), 2017 IEEE*, pages 180–185. IEEE, 2017.
[7] J. A. Sauter, R. Matthews, H. V. D. Parunak, and S. A. Brueckner. Performance of digital pheromones for swarming vehicle control. In *Proceedings of the Fourth International Joint Conference on Autonomous Agents and Multiagent Systems*, pages 903–910. ACM, 2005.
[8] M. Ahuja. Fuzzy Counter Ant Algorithm for maze problem. Master's thesis, University of Cincinnati, 2010.
[9] J. Cao. Robot global path planning based on an Improved Ant Colony Algorithm. *Journal of Computer and Communications*, 4(02):11, 2016.
[10] T. S. Rappaport et al. *Wireless communications: principles and practice*, volume 2. Prentice Hall PTR New Jersey, 1996.