

Hybrid Gravity Gradient Inversion-Ant Colony Optimization Algorithm for Motion Planning of Mobile Robots

Meng Wu

Abstract—Motion planning is a common task required to be fulfilled by robots. A strategy combining Ant Colony Optimization (ACO) and gravity gradient inversion algorithm is proposed for motion planning of mobile robots. In this paper, in order to realize optimal motion planning strategy, the cost function in ACO is designed based on gravity gradient inversion algorithm. The obstacles around mobile robot can cause gravity gradient anomalies; the gradiometer is installed on the mobile robot to detect the gravity gradient anomalies. After obtaining the anomalies, gravity gradient inversion algorithm is employed to calculate relative distance and orientation between mobile robot and obstacles. The relative distance and orientation deduced from gravity gradient inversion algorithm is employed as cost function in ACO algorithm to realize motion planning. The proposed strategy is validated by the simulation and experiment results.

Keywords—Motion planning, gravity gradient inversion algorithm, ant colony optimization.

I. INTRODUCTION

MOTION planning and obstacle avoidance are the two related areas of research with broad commercial and military applications. How to do motion planning and obstacle avoidance effectively is still a major challenge in autonomous navigation field nowadays [1], [2].

Over past decades, object detection algorithms based on gravity gradient and magnetic anomaly have been researched widely [3]-[7]. Gravity gradient inversion algorithm is widely applied into underwater object detection. In [4], gravity gradient inversion method is firstly applied to detect abnormal underwater objects in underwater environment. In [5], gravity tensor and gravity gradient tensors are combined to realize passive subsurface underwater object detection. In [7], gravity gradient differential and the gravity gradient differential ratio caused by the relative motion between the AUV and the underwater object is applied to realize underwater object detection.

ACO is an evolutionary algorithm and it has ability to solve some difficult problems in the optimization path planning of mobile robots [8]. In [9], ACO algorithm is utilized to find the shortest and collision-free route between a starting point and a destination point in a grid network. In [10], ACO is applied to robot path planning in a dynamic environment. Two different pheromone re-initialization schemes are compared. In [11],

authors adopt ACO to establish an effective UAV path planning scheme under obstacle-avoidance constraint. In [12], Rong Du et al. present so-called I-ACO (Improved ACO) algorithm to do path planning and collision avoidance. They divide the I-ACO into two modes, one is approaching mode and another is capturing mode, such strategy provides the path planning methods with direction factor to keep the pursuers tracking the evaders, and a blocking rule is introduced to prevent the virtual ants from moving to a place repeatedly. In [13], ACO algorithm is successfully applied in complex environment to help mobile robots to avoid obstacles.

In this paper, gravity gradient inversion algorithm is combined with ACO to do motion planning and obstacle avoidance for mobile robots.

This paper is organized as follows. In Section II, system architecture of this platform is introduced and analyzed. In Section III, motion planning algorithm based on joint gravity gradient inversion and ACO is introduced and analyzed. In Section IV, simulation results are discussed. Conclusions are summarized in Section V.

II. SYSTEM OVERVIEW

The general system architecture of the proposed motion planning strategy is shown in Fig. 1. In this paper, ACO algorithm and gravity gradient inversion algorithm are combined to realize motion planning and obstacle avoidance. The proposed algorithm in this paper can find a shortest and collision-free path for mobile robots. The flow chart is shown in Fig. 1.

The general system architecture of the proposed motion planning strategy is shown in Fig. 1. Assuming a fact that a gradiometer is installed on each ant in ACO, when each ant moves from nest to the destination where food is available, gravity gradient inversion algorithm is employed to calculate a relative distance between the ant's current location and its destination. In this paper, gradiometer installed on each ant in ACO can detect gravity gradient anomalies caused from the ant's destination, under such assumption, gravity gradient inversion algorithm is implemented to obtain the relative distance of the ant's destination, then, the distance is employed into heuristic function in ACO to realize motion planning.

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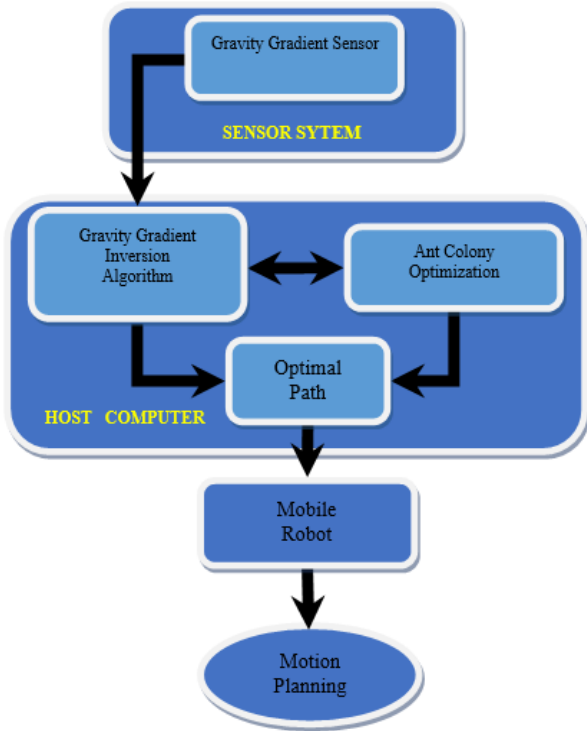


Fig. 1 Flow-Chart of Motion Planning Algorithm based on ACO combined with Gravity Gradient Inversion Method

III. DESCRIPTION OF PROPOSED ALGORITHM

A. Introduction of ACO

Animals such as ants and honeybees have an ability to manage to establish shortest path from their nest to the food location and back to the nest by group cooperation. In this paper, virtual ants can deposit pheromone during their return to the nest. Imagining a fact that a gradiometer is installed on each virtual ant, gravity gradient anomalies which are caused from the location of food can be detected. After obtaining values of gravity gradient anomalies from the gradiometer, each virtual ant can know the relative distance and direction of the food. In this paper, gravity gradient tensors are introduced as heuristic information into ACO.

When ACO combined with gravity gradient inversion algorithm is implemented, a group of individual ants is created. These ants will explore a grid-based map. When an ant is exploring the grid map, there are several possible ways to follow at every point in the map [13]. A probabilistic way is employed for each ant to choose path, and the probability for a path to be chosen is determined by each ant's pheromone concentration and heuristic information, which is illustrated in (1) and [13] as:

$$p_{ij}^k = \begin{cases} \frac{(\tau_{ij}^k)^\alpha (\eta_{ij}^k)^\beta}{\sum_{l \in N_i^k} (\tau_{il}^k)^\alpha (\eta_{il}^k)^\beta} & j \in N_i^k \\ 0 & j \notin N_i^k \end{cases} \quad (1)$$

in which: p_{ij}^k = probability of ant k to choose a path from i to j , τ_{ij}^k = pheromone concentration in the path from i to j , N_i^k = neighboring nodes of ant k where its location is at node i , η_{ij}^k = heuristic information known about the path between i and j , α & β = representation of influence the pheromone concentration and the heuristic information in the decision of a virtual ant. d_{ij}^k = the distance between i and j , $\Gamma_{ant^k(x,y,z)}$ = gravity gradient anomalies caused from location of food.

The pheromone deposited on the grid map from node i to j is subjected to evaporation, which means its concentration decays over time, and the decay is represented by (2):

$$\begin{cases} \tau_{ij}(t+n) = \rho \tau_{ij}(t) + \Delta \tau_{ij} \\ \Delta \tau_{ij} = \sum_{k=1}^m \Delta \tau_{ij}^k \\ \Delta \tau_{ij}^k = \frac{Q}{L_k} \end{cases} \quad (2)$$

in which: $\tau_{ij}(t+n)$ = "intensity of trail" between node i and node j at time $t+n$, ρ = evaporation ratio which represents how much information is left between iterative time t and $t+n$, $\Delta \tau_{ij}$ = sum of all m ants' pheromone laid on the edge between i and j during iterative time between t and $t+n$, $\Delta \tau_{ij}^k$ = k th ant's pheromone laid, Q = pheromone gain which is a constant, L_k = k th ant route length

In this paper, heuristic information arises from the Euclidean distance between node i and j .

$$\begin{cases} d_{ij}^k = \sqrt[3]{\frac{GM}{\Gamma_{ant^k(x,x)} + \Gamma_{ant^k(y,y)}} \left(1 - \frac{3}{\left(\frac{\Gamma_{ant^k(x,y)}}{\Gamma_{ant^k(y,z)}}\right)^2 + \left(\frac{\Gamma_{ant^k(x,y)}}{\Gamma_{ant^k(x,z)}}\right)^2 + 1}\right)} \\ \eta_{ij}^k = \frac{1}{d_{ij}^k} \end{cases} \quad (3)$$

in which: d_{ij}^k = Euclidean distance between node i and j , ant k is located at node i , G = Gravitational constant, M = mass of an obstacle located in node j , η_{ij}^k = heuristic information; $\Gamma_{ant^k(x,y,z)}$ = gravity gradient anomalies caused by an obstacle at

node j where we could apply gravity gradient inversion algorithm to calculate the relative distance between node i and node j . Assuming a fact that an ant k is planning to move from node i to its neighbor nodes, the gradiometer installed on the ant k can detect gravity gradient anomalies caused by an obstacle located at any neighbor node. if the distance is less than radius of obstacle, the ant k will make a decision to go to other nodes instead of the node where there is an obstacle. The details of the algorithm are shown in Fig. 2, and the gradiometer is employed to judge relative distances between the mobile robot and its neighbor obstacles.

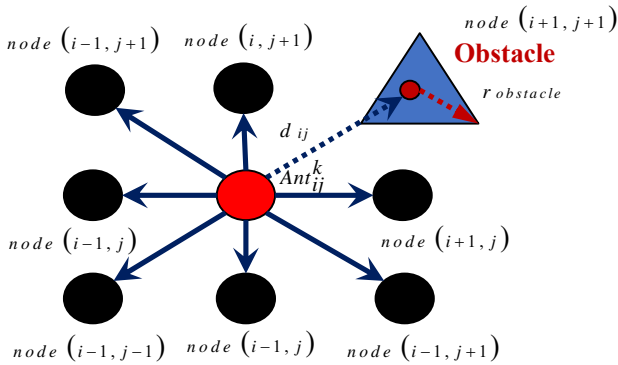


Fig. 2 Graphical Representation of ant k 's path planning to avoid obstacle which is located in neighbour nodes

B. Flow Diagram of Geophysical-Based ACO Algorithm

In Fig. 3, the flow diagram shows how mobile robot modifies its tabu table to find an optimal path and avoid obstacles. The gradiometer is to detect relative distance between the mobile robot and its neighbor obstacles, then, the distance can be employed to build tabu table in ACO algorithm.

IV. SIMULATION AND RESULTS

In this simulation, gravity gradient inversion algorithm is combined into ACO method to realize motion planning for mobile robots. The simulation is based on a grid map which is 20×20 , the cell size is 25 m. The simulation result is shown in Fig. 4. In Fig. 4, when we set the iteration times as 200 Times, ACO combined with gravity gradient inversion algorithm is a good solution to find shortest path efficiently within complex obstacles and shows a good performance in motion planning.

V. CONCLUSION

This paper proposed a motion planning approach for mobile robots using gravity gradient inversion algorithm and ACO algorithm. Specifically, the heuristic function in ACO is designed based on gravity gradient inversion algorithm. A shortest and collision-free path is obtained based on the method proposed in this paper. The simulation clearly demonstrates the efficacy of the proposed approach, which successfully achieves very high levels of motion planning and obstacle avoidance.

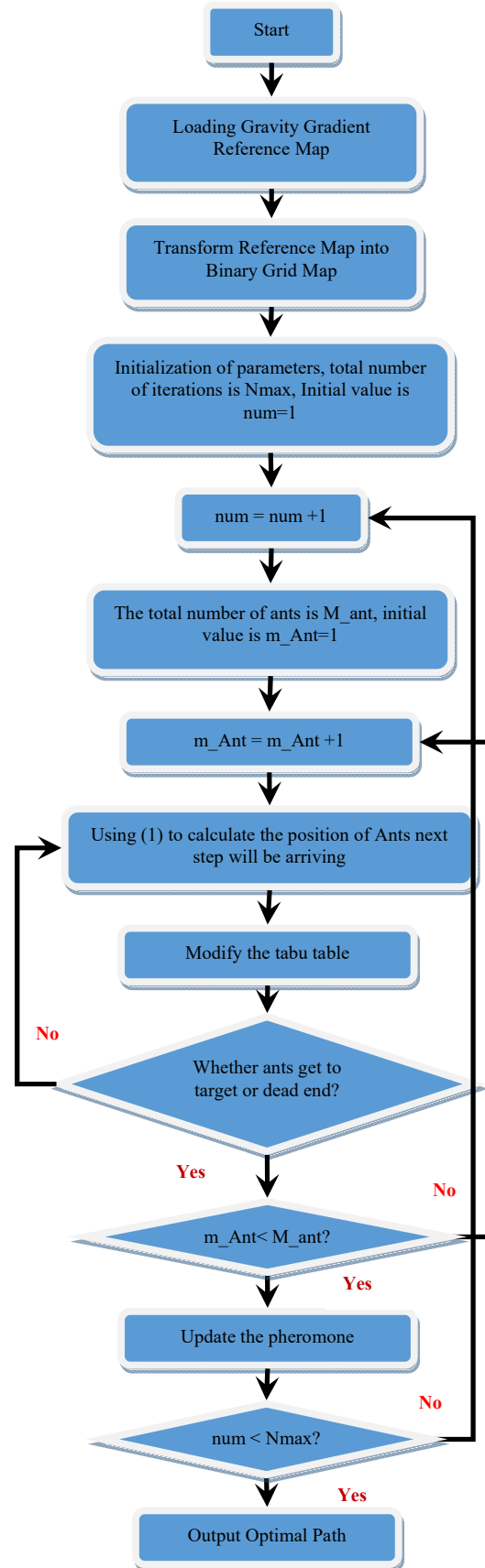


Fig. 3 Flow diagram of ACO combined with Gravity Gradient Inversion Algorithm

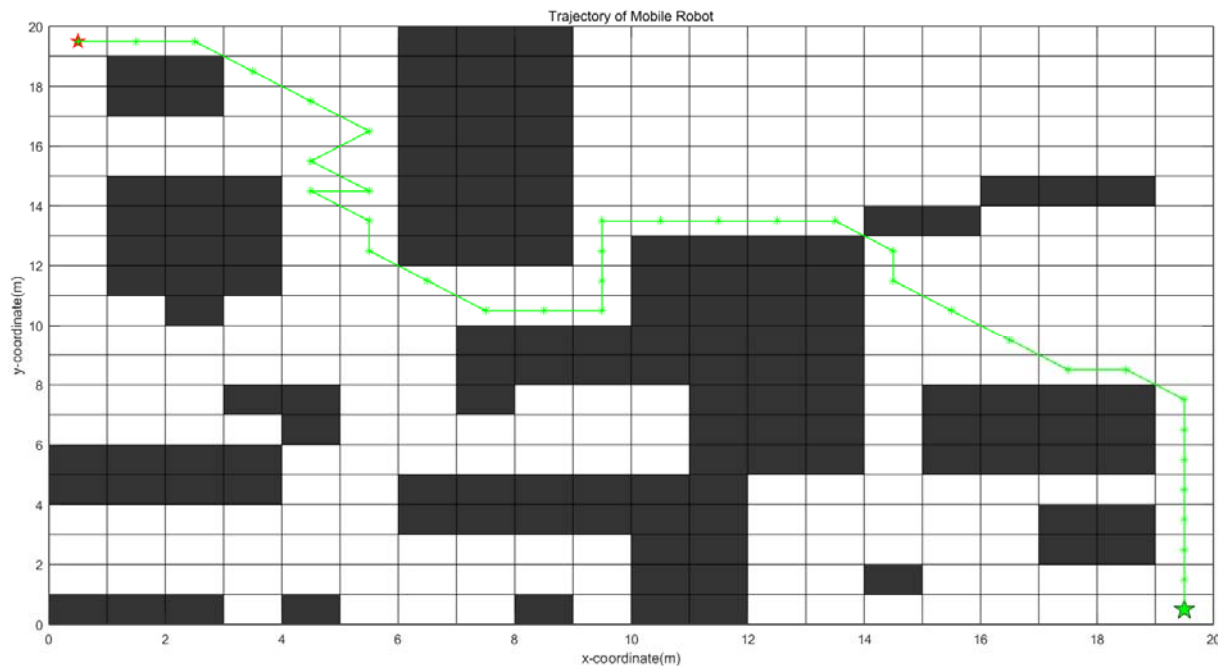


Fig. 4 Simulation Result based on ACO and Gravity Gradient Inversion Algorithm

REFERENCES

[1] G. J. Heald and H. D. Griffiths, "A review of underwater detection techniques and their applicability to the landmine problem". in Proc.2nd Int. Conf. Detection Abandoned Land Mine, pp.173-176, 1998.

[2] Ling Xiong, Jie Ma, Jin-wen Tian. "Gravity Gradient Aided Position Approach Based on EKF and NN". 2011 Cross Strait Quad-Regional Radio Science and Wireless Technology Conference, pp. 1347-1350, July.2011.

[3] H. Zheng, H. Wang, L. Wu, H. Chai, Y. Wang. "Simulation Research on Gravity-Geomagnetism Combined Aided Underwater Navigation". Royal Institute of Navigation, vol. 66, No. 1, pp. 83-98, 2013.

[4] L. Wu, X. Tian, J. Ma, and J.W. Tian, "Underwater object detection based on gravity gradient," IEEE Geosci. Remote Sens. Lett., vol. 7, no.2, pp.362-365, Apr.2010.

[5] L. Wu, X.P. Ke, H. Hsu, J. Fang, C.Y. Xiong, and Y. Wang, "Joint gravity and gravity gradient inversion for subsurface underwater object detection," IEEE Geosci. Remote Sens. Lett., vol. 10, no.4, pp.865-869, Jul.2013.

[6] L. Wu and J.W.Tian, "Automated gravity gradient tensor inversion for underwater object detection," J. Geophys. Eng., vol. 7, no. 4, pp. 410-416, Dec.2010.

[7] Zu Yan, J.Ma, Jinwen Tian, Hai Liu, Jinggang Yu, and Yun Zhang "A Gravity Gradient Differential Ratio Method for Underwater object Detection," IEEE Geosci. Remote Sens. Lett., vol. 11, no.4, pp.833-837, Apr.2014.

[8] Song-Hiang Chia, Kuo-Lan Su, Jr-Hung Guo, Cheng-Yun Chung." Ant Colony System Based Mobile Robot Path Planning", 2010 Fourth International Conference on Genetic and Evolutionary Computing, pp. 210-213, 2010.

[9] Michael Brand, Michael Masuda, Nicole Wehner and Xiao-Hua Yu. "Ant Colony Optimization algorithm for robot path planning", 2010 International Conference on Computer Design and Applications, pp. V3-436-V3-440, 2010.

[10] Zhang Chibin, Wang Xingsong and Du Yong. "Complete Coverage Path Planning Based on Ant Colony Algorithm", 2008 15th International Conference on Mechatronics and Machine Vision in Practice, pp. 357-361, 2008.

[11] Jie Chen, Fang Ye and Tao Jiang. "Path Planning under Obstacle-Avoidance Constraints Based on Ant Colony Optimization Algorithm", 2017 17th International Conference on Communication Technology (ICCT), pp. 1434-1438, 2017.

[12] Rong Du, Xiaobin Zhang, Cailian Chen and Xingping Guan. "Path Planning under Obstacle-Avoidance Constraints Based on Ant Colony Optimization Algorithm", 2010 IEEE/ACM International Conference on Cyber, Physical and Social Computing, pp. 768-773, 2010

[13] Ronald Uriol, Antonio Moran. "Mobile Robot Path Planning in Complex Environments Using Ant Colony Optimization Algorithm", 2017 3rd International Conference on Control, Automation and Robotics (ICCAR), pp: 15-21, 2017.