Multi-goal Motion Planning of an Autonomous Robot in Unknown Environments by an Ant Colony Optimization Approach

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Abstract. An ant colony optimization (ACO) approach is proposed in this paper for real-time concurrent map building and navigation for ***multiple goals*** purpose. In real world applications such as rescue robots, and service robots, an autonomous mobile robot needs to reach multiple goals with the shortest path that, in this paper, is capable of being implemented by an ACO method with minimized overall distance. Once a global path is planned, a foraging-enabled trail is created to guide the robot to the multiple goals. A histogram-based local navigation algorithm is employed locally for obstacle avoidance along the trail planned by the global path planner. A re-planning-based algorithm aims to generate path while a mobile robot explores through a terrain with map building in ***unknown*** environments. In this paper, simulation results demonstrate that the real-time concurrent mapping and multi-goal navigation of an autonomous robot is successfully performed under *unknown* environments.

Keywords: Ant colony optimization · Multi-goal motion planning · Autonomous robot · Mapping · Unknown environments

1 Introduction

Motion planning and mapping of autonomous robots is an important issue. Concurrent motion planning and mapping of robotics is to search a suitable collision-free path of an autonomous robot to move from an initial position to a goal designation while the robot builds up a map, in an unknown environment. Research on such point-to-point robot motion planning has been well carried out recently, indeed, which is a sort of single-goal navigation. In real-time world applications, such as rescue robots, service robots, mining rescue robots, and mining searching robots, etc., multi-goal motion planning of autonomous robots is highly desirable. In addition to the service robots, many other robotic applications require multi-goal navigation such as vacuum robots, land mine detectors, lawn mowers, and windows cleaners. The multi-goal path planning aims to search a collision-free path for visiting a sequence of goals with the minimized total route under unknown environments.

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There have been a large number approaches proposed on autonomous robot motion planning [1–7]. Gu *et al.* [1] proposed an elastic-band-based motion planning model, in which tunability and stability are focused on the robot navigation. Raja *et al.* [2] suggested a gradient function in the conventional potential field method associated with a Genetic Algorithms (GA) based method for robot motion planning. Besides an attractive force, a repulsive force, a tangential force and a gradient force are introduced in the conventional potential field method integrated with a GA path planning model. Davies and Jnifene [3] developed a GA path planner to guide an autonomous robot to reach specified multiple goals with obstacle avoidance. However, a couple of artificial waypoints have to be necessarily predefined to assist in preventing the robot from the deadlock or escaping from the local minima, which causes more timing delay, more length and more cost.

Luo and Yang [4, 5] developed a bio-inspired neural network model that concurrently performs mapping and path planning tasks. Yang and Meng [6] proposed a biologically inspired neural network approach to real-time collision-free motion planning of mobile robots in a non-stationary environment. However, multi-goal navigation studies have not been performed largely for intelligent robot systems. Faigl and Macak [7] developed a self-organizing map method in conjunction with an artificial potential field based navigation function to generate an optimal path of a mobile robot to visit multiple goals, through a Traveling Salesman Problem (TSP) tool. The autonomous robot visits multiple targets just as the traveling salesman problem but with the presence of obstacles, in which mobile robots are navigated with the discrete map representation filled with some exact cell in workspace. Although a multi-goal navigation model of an autonomous robot modeled as a point robot by ACO is implemented by Gopalakrishnan and Ramakrishnan [8], the model lacks of map building component, neither.

In this paper, a real-time concurrent multi-goal motion planning and map building approach of an autonomous robot in *completely unknown environments* is proposed. A local map composed of cells is dynamically built through the histogram-driven local navigator with restricted sensory information such as LIDAR-based data while it is navigated under completely unknown environments with obstacle avoidance to visit multiple requested goals. The sensory information obtained by onboard sensors mounted on the robot is utilized for obstacle avoidance in unknown sceneries.

2 Histogram-Based Local Navigator and Cell-Based Map Building

The navigation system consists of two layers, one is a D*-Lite global path planner with re-planning function and the other is a histogram-based local navigator. Flexibility and efficiency motivate D*-Lite to be adapted to multi-goal path planning. D*-Lite is an incremental heuristic search algorithm extended from A* algorithm by re-utilizing previous search effort in subsequent search iterations for efficient re-planning [9]. A* utilizes a best-first search from a starting point **S*start*** to the goal **S*goal*** guided by the heuristic h thus it is able to search an efficiently traversable path between points commonly employed for robotics path planning in known 2D gird-based maps [10].

In this paper, the D*-Lite is employed to generate the global trajectory of an autonomous robot under unknown environments.

The local navigator aims to generate velocity commands for the autonomous mobile robot to move towards a goal. The inclusion of a sequence of markers in the motion planning, which decomposes the global trajectory into a sequence of segments, makes the model especially efficient for the workspace densely populated by obstacles. Ulrich and Borenstein [11] first successfully proposed a Vector Field Histogram (VFH) methodology for navigation. The Virtual Force Field (VFF) approach was initially inspired by potential field method in conjunction with the concept of certainty cells [11, 12]. In this paper, VFH is utilized as our LIDAR-based local navigator. 2D cell-based map filled with cells [12], which are marked as either occupied or free, is built as the mobile robot moves. It is especially beneficial for autonomous robots to perform robust multi-goal navigation in unknown terrains, given the fact that it facilitates the utilization of path planning algorithms to determine the optimal trajectory among waypoints as multiple goals.

3 ACO-Based Multi-goal Visit

In real world applications of multi-goal navigation and mapping, multiple goals as a sequence of waypoints and a relative cost for travelling between each goal to each other are provided. The objective is to search a route through all the waypoints in which all waypoints are visited once, and to find the shortest overall tour. In rescue robot application, for instance, the robot starts at one designated waypoint, visits each other waypoint and then ends at the initial waypoint. Traveling Salesman Problem (TSP) is an optimization problem to minimize the travelling distance in a finite number of cities while the cost of travel between each city is known. The classic TSP is employed to deal with the multi-goal visit problem, in which a sequence of goals is visited so that the total planned length of the route is minimized. The objective of this TSP with regard to multi-goal navigation is to search an ordered set of all the waypoints for the autonomous robot to visit at such that the cost is minimized. A list of waypoints and distances, or cost, between each of them is necessary for TSP. Therefore, goals are called waypoints with GPS coordinates of the goals in latitude and longitude. The multi-goal visit problem has practical applications on some fields such as transportation plan issues where deliveries are required as well as fuel cost and time are to be minimized.

In this paper, ant colony optimization (ACO) is utilized to resolve the TSP for the multi-goal navigation with multiple waypoints [13] programmed in MATLAB. Ants in ACO are agents in the TSP, which traverse from one waypoint to another waypoint navigated by pheromone trails and an a priori available heuristic information. Ant pheromone strength $\tau_{ij}(t)$, a numerical information, defined with each arc (*i*, *j*) is updated in the ACO algorithm for TSP, where *t* is the iteration counter. The agent is initially placed in a waypoint. At each iteration step, a probabilistic action choice rule is applied to an agent, hereafter, a mobile robot, *k*. The probability of a robot k, currently at waypoint *i*, which moves to waypoint *j* at the *t*th iteration of the algorithm, is obtained as follows.

$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \times [\vartheta_{ij}]^{\beta}}{\sum_{l \in \aleph_i^k} [\tau_{il}(t)]^{\alpha} \times [\vartheta_{il}]^{\beta}} \text{ if } j \in \aleph_i^k \tag{1}$$

where, $\aleph_i^k$ is the feasible adjacent waypoint of robot k, the set of cities which the robot k has not visited yet. Parameters α and β determine the relative influence of the pheromone trail and the heuristic information. $\vartheta_{ij} = 1/d_{ij}$ is an a *priori* available heuristic value, and d_{ij} is the distance between two waypoints. Parameter α represents importance factor of the pheromone, which matches a classical stochastic greedy algorithm. Parameter β is an importance factor of the heuristics function. If the larger parameter β becomes, the more likely it is that the robot moves to the closest waypoint driven by the heuristic function. If a parameter ρ is defined as the pheromone trail evaporation, $0 < \rho < 1$ to prevent the pheromone trails from accumulating unlimitedly; it is able to allow the ACO algorithm to ignore unreasonably bad decisions previously made.

At each iteration step, $\Delta\tau_{ij}^{k}(t)$, the amount of pheromone robot k places on the arcs it has visited is dynamically updated by decreasing the pheromone strength on all arcs by a constant factor before enabling each robot to supplement pheromone on the arcs. The pheromone strength τ_{ij} is dynamically updated as follows.

$$\begin{cases} \tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij} \\ \Delta\tau_{ij} = \sum_{k=1}^{n} \Delta\tau_{ij}^{k} \end{cases}, 0 < \rho < 1 \tag{2}$$

where, the amount of pheromone $\Delta\tau_{ij}^{k}(t)$, is defined as three modes [13]:

(1). Ant cycle system mode:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L^k(t)} & \text{if arc}(i,j)\text{is ued by robot}k \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

(2). Ant quantity system mode:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{d_{ij}(t)} & \text{if arc } (i,\, j)\text{is ued by robot } k \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} Q & \text{if arc } (i,j)\text{is ued by robot}k \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

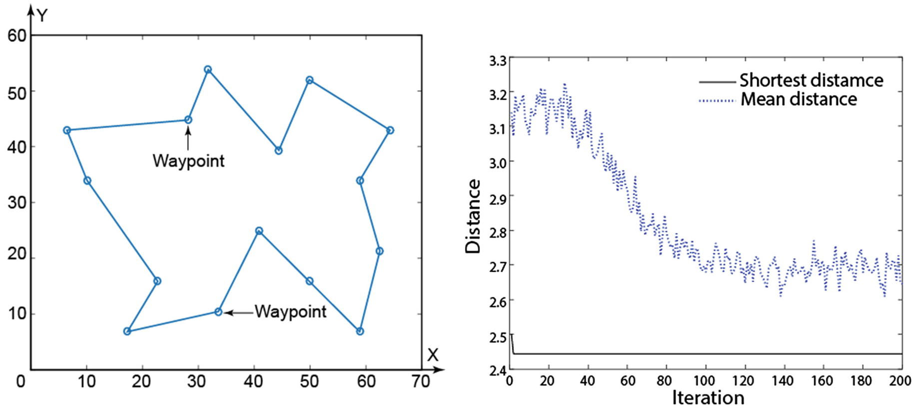
(3). Ant density system mode:

$L^k(t)$ is the length of the kth robot's tour. $d_{ij}(t)$ is the distance between waypoints i and j. Q is constant representing the total amount of pheromone. The ACO algorithm for TSP to visit multiple waypoints is summarized as Fig. 1 [13].

```
procedure ACO algorithm for TSPs
    Set parameters, initialize pheromone trails
    while (termination condition not met) do
        ConstructSolutions
        ApplyLocalSearch
        UpdateTrails
    end
end ACO algorithm for TSPs
```

Fig. 1. ACO algorithm for TSP with multiple waypoints

After execution of this ACO-based TSP algorithm with the method (1), the minimized total route to connect all the waypoints is obtained. There are fifteen waypoints in the workspace that required a service mobile robot to reach per waypoint. The ACO-based TSP algorithm is applied to this application illustrated in Fig. 2(a). The shortest and mean distances acquired are depicted in Fig. 2(b).



(a) (b)

Fig. 2. ACO algorithm for TSP applied in a 15-waypoint workspace, (a) TSP route; (b) The shortest and mean distances over iterations

4 Real-Time Concurrent Map Building and Multi-goal Navigator

Given a set of waypoints as multiple goals and possible starting points, a matching ***lookup table*** for waypoint sequencing is created. The D*-Lite algorithm then provides an initial path marked by markers between pairs of goals, and the VFH navigation algorithm drives the robot alone those markers. A sort of multi-layer software development environment is implemented based on Player/Stage™.

An actual autonomous robot was developed as test-bed for our hybrid system of real-time concurrent multi-goal navigation and map building of an autonomous robot. The robot incorporates six sensors into its compact design as follows: a LIDAR, a DGPS, a digital compass, a camera, and an IMU, each of which is enclosed in a waterproof case and firmly mounted to the robot. A 270° SICK LMS111 LIDAR is configured for the purposes of obstacle detection illustrated.

5 Simulation Studies

In this section, the proposed real-time concurrent multi-goal navigation and mapping of an autonomous robot in unknown environments will be validated on Player/Stage™ simulator.

5.1 Real-Time Concurrent Multi-goal Navigation and Map Building in Unknown Environments Without Obstacles

In order to validate the effectiveness and efficiency of the proposed hybrid system, the model is applied to simulate an autonomous robot under unknown environments in a 15-goal course. The robot is navigated to connect 15 waypoints in a free-space to test the ACO-based multi-goal model with mapping illustrated in Fig. 3. The robot is able to traverse from the initial point to plan the shortest route to visit the 15 waypoint while the robot builds the map with 270° LIDAR. The rout of multi-goal by the robot is shown in Fig. 3(a) whereas the map built is illustrated in Fig. 3(b) at the end of the travel of the robot.

5.2 Navigation in a 15-Goal Course with Obstacle Avoidance

In this simulation, the robot is guided in an unknown environment populated with obstacles with 15 waypoints as multiple goals depicted in Fig. 4(a), which shows that the robot traverses from starting waypoint to connect 15 waypoints obtained by GPS coordinates. The built map while the robot moves in the unknown environment with 270° LIDAR scan is illustrated in Fig. 4(b) while the robot moves on the road from waypoint from waypoint. The black portions are detected obstacles with blue line of the robot path in Fig. 4(b).

In accordance with the planed trajectory, the GPS coordinates of the targets in latitude and longitude in sequence of the goals is dispatched to the D*-Lite based global path planner. As described in the previous sections, from one goal to another goal, the VFH based local navigator is utilized to navigate the robot by following pre-placed markers. Starting from the initial point, the autonomous robot is capable of travelling to the sequence of goals based on the proposed multi-goal navigation system and simulation studies were successfully accomplished.

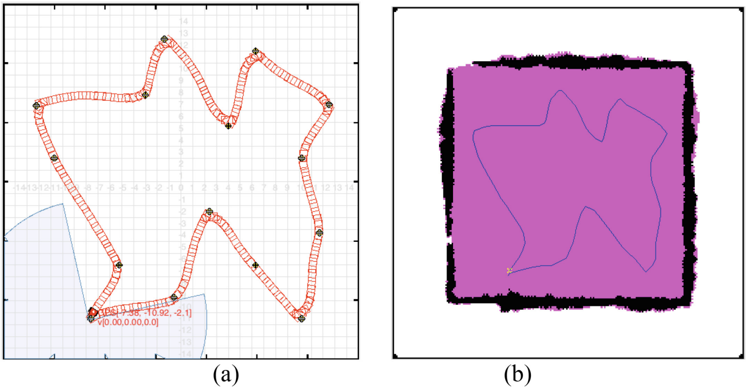


Fig. 3. Simulation result of the robot in unknown workspace. (a) The workspace with obstacles and 15 goals; (b) Built map.

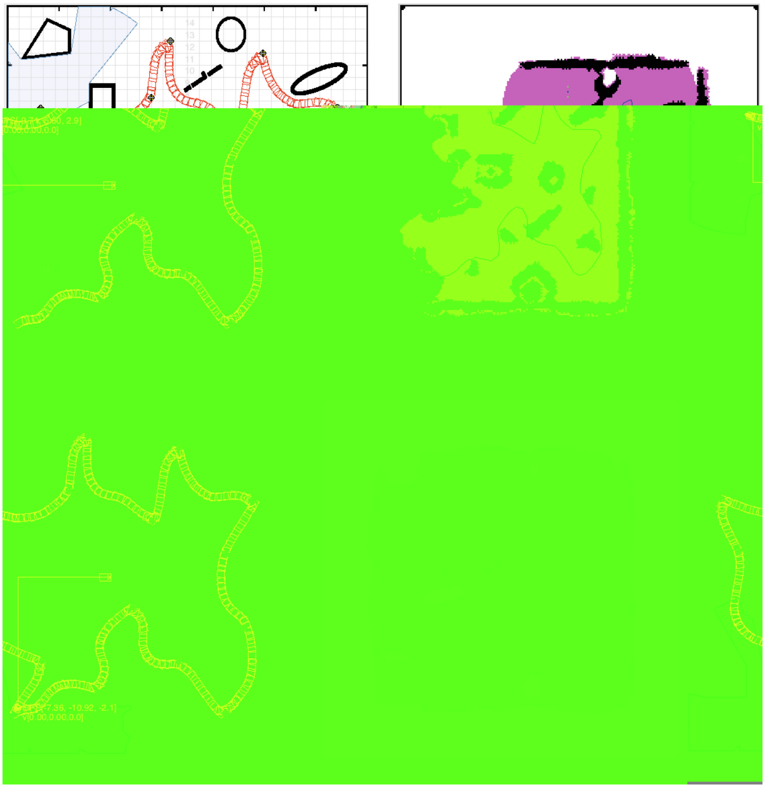


Fig. 4. Multi-goal navigation and mapping by the LIDAR in the ACO-based method, (a) Route planned by the proposed ACO-based TSP model; (b) Built map by the LIDAR; (c) Route planned at the end; (d) Built map by the LIDAR at the end. (Colour figure online)

After the route to visit these fifteen waypoints is generated by the proposed ACO-based TSP algorithm, the GPS coordinates of the targets in latitude and longitude in sequence of the goals are transmitted to the global path planner in Fig. 4. Once a path from D* Lite has been obtained that was early generated by the ACO-based TSP algorithm, a number of points along it are extracted so as to use the VFH algorithm between two goals. These points as markers are converted into GPS coordinates and presented to VFH as consecutive points. VFH then generates motion commands which are transmitted to the drive controllers to move the robot towards these intermediate waypoints. Once the robot approaches to an intermediate waypoint, the next intermediate goal along the desired path is regarded to be achieved and substituted. In Fig. 4 (c), the autonomous robot returns the starting point after it traverses from starting waypoint to every goal by planning a collision-free trajectory to connect these 15 goals with minimized overall distance in Fig. 4(d).

6 Conclusion

A solution by hybrid algorithms was developed in this paper for real-time map building and navigation for multiple goals purpose. In this paper, an alternate approach, the D*-Lite algorithm associated with a local LIDAR-based navigation methodology was developed for multiple goals. The D*-Lite path planning algorithm was used to provide VFH with intermediate goals. The multi-goal route was calculated and planned by the proposed ACO-based TSP strategy. Results from simulation studies demonstrated the benefits of the local navigator in conjunction with a path planner to reach multiple goals with minimized total distance.

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