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Annealing-based Guidance of a Rescue Robot for Rescue Mission with Multi-goal Navigation

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***Abstract* - Mission of a rescue robot is to search for some certain points and find trapped people or valuables to be rescued in an unknown terrain. A rescue robot should be able to be navigated to multiple goals. In this paper, a multi-goal navigation and mapping solution is found by simulated annealing (SA) based multi-goal navigation integrated a local navigator. The robot is guided by SA-based multi-goal route planner to search for multiple goals. Among goals, the robot is navigated by point-to-point global path planner and sensor-based local navigator while a local map is constructed gradually by exploring the unknown terrain. The simulation studies demonstrate the proposed integrated methodology is efficient, effective, and robust.**

Index Terms - Simulated annealing; multi-goal navigation; sensor-based navigator; mapping; global path planner.

I. INTRODUCTION

Your Real-time robot navigation and map building is a challenging task for autonomous mobile robots, especially in unknown and dynamical environments. Path planning and map building is one of the issues in the field of robotics that attempts to find and optimize the path from the initial position to the final position while the local map is dynamically built up as the robot moves. There have been a large number of studies on navigation and building of an autonomous mobile robot by a variety of methodologies such as Genetic algorithms ([1,7]), electric charge method ([2]), map-based method ([3]), neural networks model ([4-5]), rapidly exploring random tree ([6]), particle swarm optimization ([7]), ant colony optimization ([8]). Tsai *et al* [1] developed parallel elite genetic algorithms model for global path planning, in which a near-optimal collision-free continuous route is generated in structured workspace. Locally, obstacle avoidance is a necessary for a robot navigation system. Rezaee and Abdollahi [2] proposed a decentralized cooperative control method for robots with obstacle avoidance by modeling each mobile robot an electric charge with repulsive forces with others to implement obstacle avoidance, inspired by an electric charge system. Meyera and Filliatb proposed a map-based navigation method. The navigation mission is fulfilled by map-learning and sensory-motor method.

Yang and Luo [4] suggested a biologically-inspired neural networks model for motion planning under known environments. Their non-learning-based neural dynamics methodology is extended to unknown workspace by simultaneous navigation and mapping [5]. Most recently, Moon and Chung [6] proposed a dual-tree rapidly exploring random tree approach for motion planning of a two-wheeled differential mobile robot, which fits in high-speed navigation.

Some researchers effectively integrated two methodologies for navigation and mapping. Tsai *et al* [7] suggested a hybrid motion planning system by integrating PSO (particle swarm optimization) and RGA (real-coded genetic algorithm) algorithm. A numerical approach and a kinematic model of the robot are explored to construct odometry. Fuzzy logic model is a powerful tool to navigate a mobile robot with obstacle avoidance ([8]). In order to improve efficiency of navigation and motion planning of mobile robot, fuzzy rule based method can be integrated with other methodologies. Garcia *et al* [8] developed an ant colony optimization method associated with a fuzzy inference system for robot navigation.

Davies and Jnifene [9] developed a Genetic Algorithm (GA) path planner to guide an autonomous robot to reach specified multiple goals with obstacle avoidance. However, a couple of *artificial* waypoints should necessarily be 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. Faigl and Macak [10] suggested a self-organizing map method in conjunction with an artificial potential field based navigation function in Traveling Salesman Problem (TSP) agent to generate an optimal path for a robot to visit multiple goals. Gopalakrishnan, and Ramakrishnan [11] implemented a multi-goal path planning model by Ant Colony Optimization of an autonomous robot modeled as a point robot. 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. However, the model lacks of map building component neither.

In this paper, a simulated annealing (SA) based real-time multi-goal navigation and mapping approach for a rescue robot is proposed. The multiple goals under unknown environments are accessible for rescue mission by a rescue robot. The minimized navigation distance for multiple goals is reached by SA methodology. A local map composed of square grids is dynamically constructed through the LIDAR-based local navigator with sensory information, 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 its real-time concurrent multi-goal navigation and map building in unknown sceneries.

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The rest of this paper is organized as follows. The SA-based multi-goal route planning is presented in Section II. Re-planning-based D*-Lite global path planner and VFH local navigator are discussed in Section III, respectively. In Section IV, the map representations of the environments and map building are introduced. The real-time concurrent map building and collision-free multi-goal navigation of the autonomous robot are reported in Section V. The simulation studies and experimental test of the autonomous robot in various unknown environments are described in Section VI. Finally, several important properties of the proposed approach are concluded in Section VII.

II. SA-BASED MULTI-GOAL ROUT PLANNING

SA is a powerful tool for optimization, known as a stochastic global optimization algorithm. In robot configuration Θ, with the initial robot configuration Θ0 corresponding to the initial position and the goal configuration Θg to the goal in the optimization procedure, a sequence of waypoints {Θ0 , Θ1 , Θ2 . ,...,Θg} constitute a connected collision-free route by SA optimization algorithm. In this paper, multi-goal route planning is inspired by Traveling Salesman Problem (TSP) solved by SA. Given a sequence of goals, considered as waypoints, with relative cost for traveling between two waypoints, the objective is to search a route through all the waypoints by visiting each waypoint once so as to find the shortest route to connect all the waypoint. The fundamental SA algorithm is summarized in Table 1 [12]. In this paper, an implicit adjacency list is utilized to represent a sequence of waypoints and tour between them [12].

Table I SA algorithm for route planning

```
Simulated Annealing Algorithms for Multi-goal Route Planning
Simulated_annealing()
{
    cur_solution = random()
    computeE(cur_solution)
    while (Temperature >0)
        adj_solution = perturb_solution(cur-solution)
        computeE(adj_solution)
        deltaE = adj_solution.energy – cur_solution.energy
    if (deltaE < 0)
            cur_solution = adj_solution
    else
            p = exp( -deltaE / Temperature )
            /* Randomly accept worse solution */
             if  ( p > RANDOM(0..1 ) )
                 cur_solution = adj_solution
             end
    end
             reduce Temperature
    end
  end simulated_annealing
    }
```

In this SA algorithm for multi-goal route planning shown in Table I, a probability is computed in Equation (1).

$$p = \exp\left(\frac{\Delta E}{T}\right) \quad (1)$$

where, T is the temperature.

III. ROBOT NAVIGATION

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 replanning. D* Lite is based on Lifelong Planning A* introduced by Koenig and Likhachev ([13]), which is an incremental replanning version of A*. 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 ([14]). The primary principle of D*-Lite in terms of incremental search is to re-utilize previous search effort in the subsequent search iterations, which represents an incremental heuristic replanning version of A*. The incremental heuristic search based D*-Lite algorithm is therefore orders of magnitude more than efficient than A* that plans a new path from scratch repeatedly. In comparison with A*, computational effort of D*-Lite with regard to search time may decrement by a factor of one to two orders of magnitude ([14]). 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 breadcrumbs in the motion planning, which decomposes the global trajectory generated by the global planner into a sequence of segments, makes the model especially efficient for the workspace densely populated by obstacles. Ulrich and Borenstein [15] 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 grids. Due largely to failure of avoiding the inherent defects of potential fields, its forward version, Vector Field Histogram (VFH) method was developed to overcome the shortcomings of VFF ([15]). Afterwards, the enhanced version of VFH approach, namely, VFH+, was introduced to take the dimension of robot into account. Use of A* search algorithm associated with heuristics and appropriate cost function, the VFH+ was evolved to VFH*. In this paper, VFH+ is utilized as our LIDAR-based local navigator.

IV. GRID-BASED MAP BUILDING

2D grid-based map filled with equally-sized grid cells, which are marked as either occupied or free, is built as the mobile robot moves. Concurrent map building and navigation are the essence of successful multi-goal navigation under unknown environments. Map building is a fundamental task in order to achieve high levels of autonomy and robustness in multi-goal navigation that makes it possible for autonomous robots to make decision in positioning with obstacle avoidance.

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. Precise estimate of the robot pose (X, Y, Yaw) is demanded by map building so that accurate registration of the local map on the global map is capable of being carried out. In addition, a Kalman Filter is implemented to estimate robot pose reliably by fusing data from the motor encoders, the DGPS, and the digital compass. This map building aims to construct a probabilistic-occupancy-grid-based map. The values for each cell in the map vary over the range [-127, 128]. The initial value is zero, which indicates that the cell is neither occupied nor unoccupied. The value is 128 if one cell is occupied with certainty and -127 if one cell is unoccupied with certainty. The values falling into (-127, 128) express contain level of certainty in between.

V. 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 breadcrumbs between pairs of goals, and the VFH+ navigation algorithm drives the robot alone those breadcrumbs. Path planning is carried out using the D*-Lite algorithm, which provides the best route between waypoints. D*-Lite can work off a partially complete map of the field, and progressively re-plans the optimal route when the map is augmented with new information as the robot explores. This is where the innovative D*-Lite debugging tool proved its worth. Although D*-Lite is a very effective algorithm to use for unknown terrain, its integration with a specific navigation task is difficult without a built-in debugging tool. Therefore, we designed a debugging tool which shows the breadcrumbs path from one waypoint to another as D*-Lite plans. Our program prints out these breadcrumbs, which update continuously according to the movement of the robot (white dots in Figure 5). Because the planned route can now be visualized by the programmers, debugging can be done by means of simulation.

A sort of multi-layer software development environment is implemented based on Player/Stage, an open-source, Unix-based robotic simulation software system, in which the proposed algorithms are developed, debugged, tested and simulated. Player provides an interface for a variety of robot and sensor peripherals accessed from local computers via a network connection to the robot whereas Stage™ is a simulation system for a robot and its environment. Since Stage™ can promptly simulate, validate and test a developing algorithm under an off-robot environment, it usually acts as a simulator with the robot, obstacles and sensors (such as LIDAR, camera, digital compass and GPS), to accelerate the development procedure of a new algorithm. Stage™ provides a powerful simulation environment that can be employed to develop and test algorithms in environments similar to those expected in an actual autonomous robot.

These multiple layers on Player/Stage provide modular isolation and enable seamless communication between software and either actual hardware or a hardware simulator possible. The first is the server layer which is occupied by Player, an open-source, Unix-based (Linux or Mac OS X) robotic software system that serves as an interface between robotic algorithm implementations and the robot systems. Specifically, it provides standard interfaces for a typical set of robotic peripherals (LIDAR, cameras, motors, etc.).

The second layer is the client layer occupied by user programs written in MATLAB. These layers communicate with Player over a TCP socket to acquire data from sensors and send actuator commands, which Player then passes on to the robot. An actual autonomous robot was developed pictured in Figure 1 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 270^0 SICK LMS111 LIDAR is configured for the purposes of obstacle detection illustrated in Figure 2. The unit is able to obtain data over a 270° field-of-view with 0.25° resolution, a maximum range of 20 m, and a 25Hz scanning rate.

Fig 1 The developed autonomous robot for the real-time concurrent multi-goal navigation and map building

The sensor configuration of our autonomous robot for multi-goal navigation and mapping is illustrated in Figure 3. The autonomous robot driven by D*-Lite global path planning in conjunction with VFH+ local navigator simulated and tested in a simple scenery with U-shaped and semi-circle obstacles on Player/Stage is depicted in Figure 4, in which the robot starts at Waypoint A(0, -21) and reaches goal at B(0, 24) with obstacle avoidance.

Fig 2 A 270^0 SICK LIDAR configured for obstacle detection

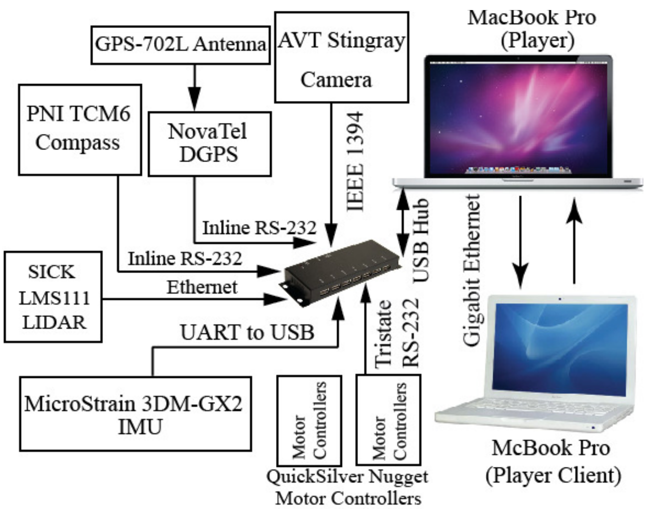


Fig 3 The sensor configuration of our autonomous robot for multi-goal navigation and mapping

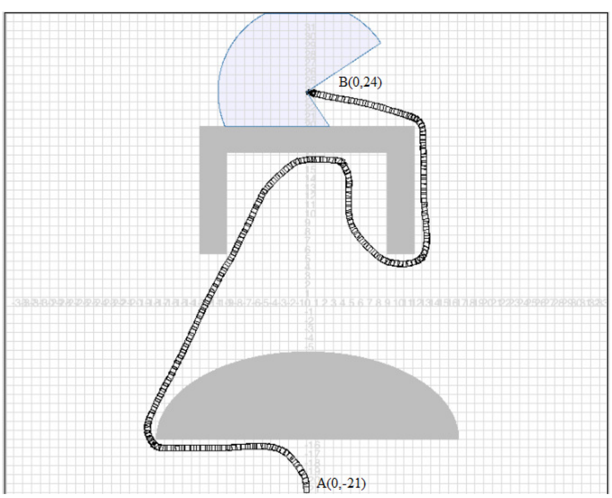


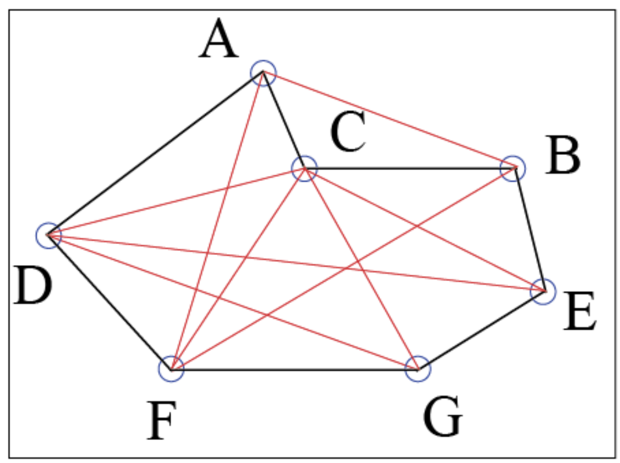
Fig 4 Simulation result in a simple U-shaped unknown environment

VI. Simulation and Experiments

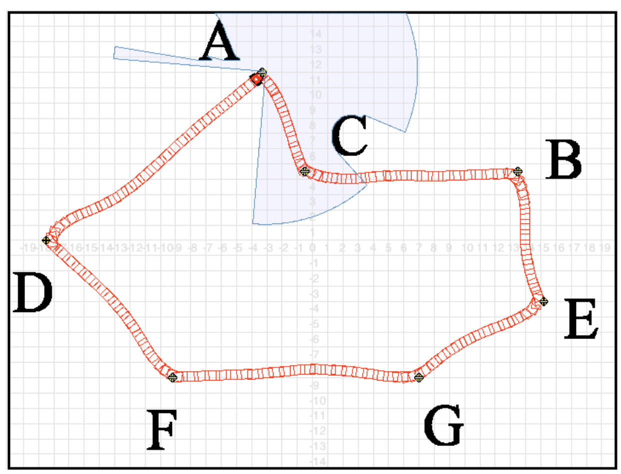
In this section, the proposed real-time concurrent multi-goal navigation and mapping of an autonomous robot in unknown environments will be validated first on Player/Stage simulator and then on an actual autonomous robot. The multi-goal is implemented in Matlab code by SA for TSP approach [16].

A. Real-time Concurrent Multi-goal Navigation and Map Building in Seven-goal Unknown Environments

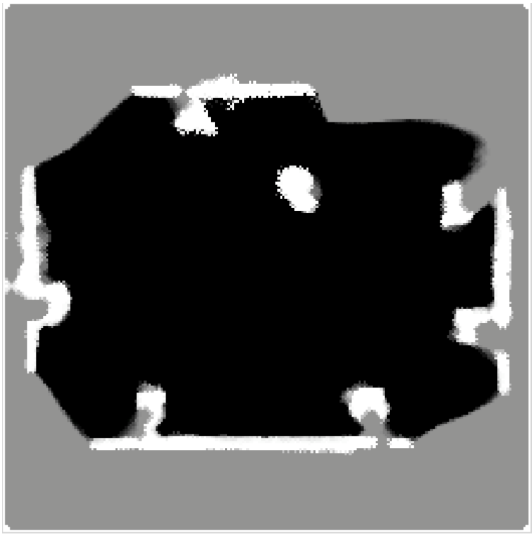
In this simulation, the robot is guided in an unknown environment populated with obstacles with nine waypoints as multiple goals depicted in Figure 5. Figure 5(A) shows that the robot traverses from starting waypoint to connect nine waypoints obtained by GPS coordinates. The final trajactry planned by SA, and VFH is illustrated in Figure (B). Figure 5(C) illustrates built map while the robot moves in the unknown environment with 270^o LIDAR scan. The black portions are detected obstacles and white dots are breadcrumbs in the map in Figure 5(B).



(A)



(B)



(C)

Fig 5 Simulation result of the robot in unknown workspace. A: The workspace with obstacles and 7 goals; B: The planned route to reach 7-goal in an unknown environment; C: The built map.

B. Real-time Concurrent Multi-goal Navigation and Map Building in Twenty-goal Unknown Environments

In order to validate the effectiveness and efficiency of the proposed hybrid system, the model is applied to simulate such real-time concurrent multi-goal navigation and map building of an autonomous robot under unknown environments in a thirty-goal course. The twenty-goal course is illustrated in Figure 6.

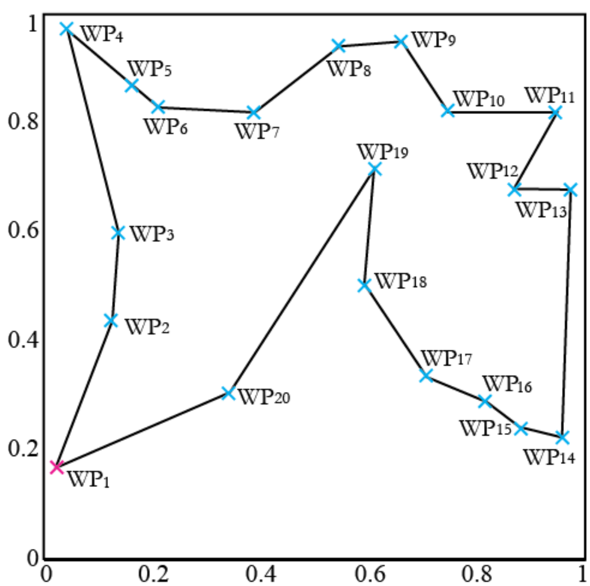


Fig 6. The workspace with obstacles and 20 goals and the planned route by SA method

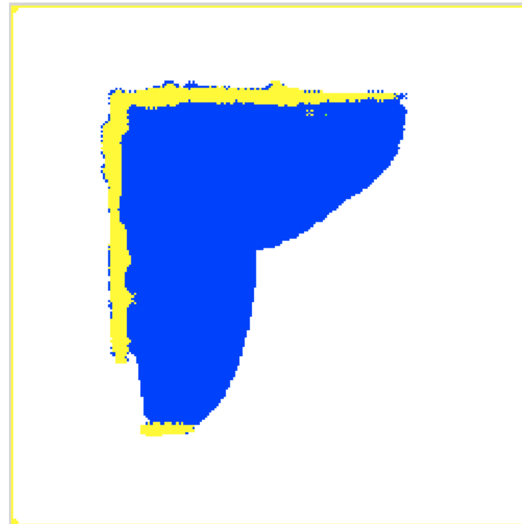


Fig 7 The constructed map at the initial phase of multi-goal navigation and mapping

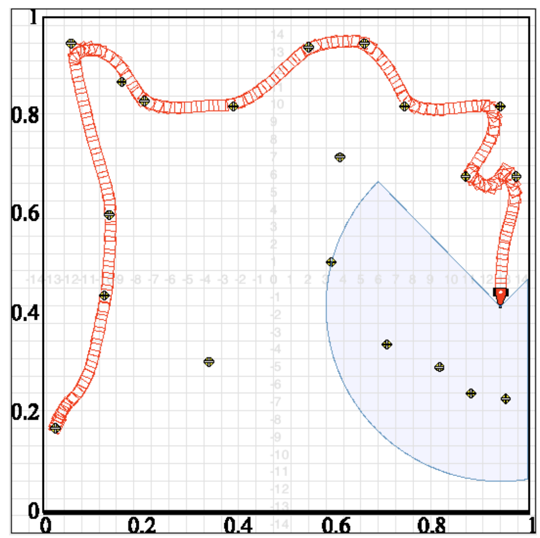


Fig 8 In the middle of planned route to connect 13-goal

After the route to visit these twenty goals is generated by the proposed SA-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 Figure 6. In the SA model, the initial temperature is set to be 2300; the cooling rate is 0.920; the Maximum iterations are set as 3600; swap cities are 3. The total distance is 4.16 units. At initial stage, LIDAR-based local navigator guides the robot to research a sequence of waypoints while local map is constructed in Figure 7.

Once a path from D* Lite is obtained that was early generated by the SA-based TSP algorithm, a number of points along it are extracted so as to use the VFH+ algorithm between two goals.

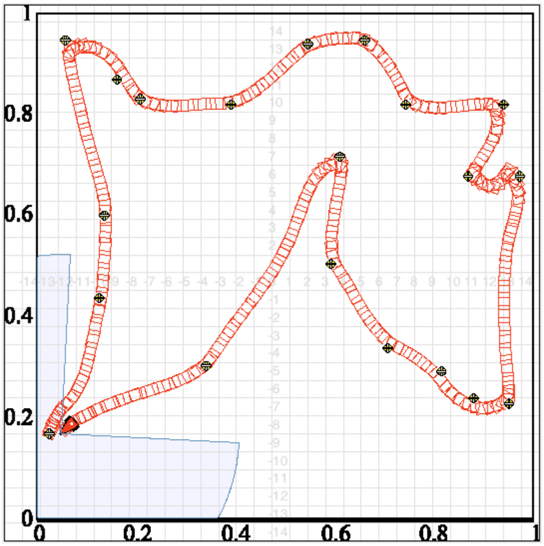


Fig 9 The planned final route to reach 20-goal in an unknown environment with SA, re-planning-based path planner and VFH local navigator

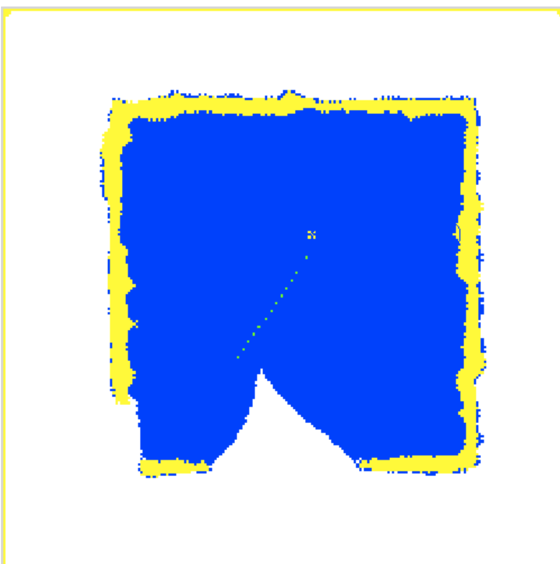


Fig 10 The constructed map based LIDAR information and VFH local navigator

These points as breadcrumbs 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 goals (waypoints). Once the robot approaches to an intermediate waypoint, the next intermediate goal along the desired path is regarded to be achieved and substituted (see Figure 8). In Figure 9, 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 thirty goals with minimized overall distance. A constructed map while the robot is guided in the unknown environment is illustrated in Figure 10.

VII. CONCLUSION

A real-time concurrent multi-goal navigation and mapping approach was developed in this paper for rescue mission by a rescue mobile robot. In this paper, an alternate approach, the D*-Lite algorithm associated with a local LIDAR-based navigator was developed for multiple goals. The multi-goal route was calculated and planned by the proposed SA-based TSP strategy. Results from simulation studies and experiments 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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