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Histogram Based Frontier Exploration

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***Abstract*—This paper proposes a method for mobile robot exploration based on the idea of frontier exploration which suggests navigating the robot toward the boundaries between free and unknown areas in the map. A global occupancy grid map of the environment is constantly updated, based on which a global frontier map is calculated. Then, a histogram based approach is adopted to cluster frontier cells and score these clusters based on their distance from the robot as well as the number of frontier cells they contain. In each stage of the algorithm, a sub–goal is set for the robot to navigate. A combination of distance transform and A* search algorithms is utilized to generate a plausible path toward the sub-goal through the free space. This way keeping a reliable distance from obstacles is guaranteed while searching for the shortest path toward the sub-goal. When such a path is generated, a B-spline interpolated and smoothed trajectory is produced as the control reference for the mobile robot to follow. The whole process is iterated until no unexplored area remains in the map. The efficiency of the method is shown through simulated and real experiments.**

***Index Terms*—Mobile Robot Exploration, Path Planning, Path Tracking**

I. Introduction

Autonomous mobile robots have many potential applications in real world that makes them attractive for researchers. Many functionalities are to be fulfilled in order to make a robot act autonomously. Among them is exploration capability which is "the ability of the robot to move through an unknown environment while building a map that can be used for subsequent navigation" [1]. The challenge stems from the fact that performance of many related algorithms such as localization, mapping, path planning, and tracking might influence the reliability and efficiency of any solution to the exploration problem. In addition, many objectives can be taken into account in proposing a method. As a result, different methods have been proposed by researchers which can be categorized based on the number and type of the robots involved in the exploration, the framework adopted and the objective sought for during the mission.

Early works like [2] and [3] in exploration field formulated the problem from graph theoretic point of view and used information from deployed active sensors to navigate the robot in the environment. Later in [4] an improvement is made by eliminating the need for localization and map building. However, all of these methods are restrained by the number of sensors that the robot could carry during the mission.

"Frontier Exploration" concept, primarily proposed by Yamauchi [1], introduced a different point of view into the problem definition and became the basis for many other methods like [5], [6], [7]. Yamauchi defined the frontiers as the boundaries between free and unknown areas in the map and set the goal of exploration as constantly navigating the robot through the selected frontiers, in his case the closest ones. Koenig and Tovey [8] have shown that such a strategy which guides the vehicle to the closest unexplored point keeps the traveled distance reasonably small compared to the shortest trajectory which covers the whole environment.

Although randomized strategies for exploration are considered in some cases (e.g. [4] and [9]), they are not guaranteed to achieve acceptable results and generally the contributions of researchers are on the selection of sub goals for robot movement during exploration. Information gain is considered in [10] and [11] for example as the basis for decision making. Such a strategy suffers from high demand of memory and computational effort. In [12] robot's current direction is integrated into the process of frontier exploration in order to maintain energy efficiency. The disadvantage of method in [12] is that it produces paths too close to walls and boundaries of obstacles and objects which makes it difficult to use their method in practice where such paths are generally unfavorable. A Multi-robot version of the exploration problem does exist and is addressed in [13], [14], [15] but it is not the focus of our work. It seems that in the context of frontier based exploration, which requires the lowest computational cost compared to other methods while yielding favorable results, the problem of choosing the next best frontier to visit can still be investigated and newer heuristics can be examined. Also, circumventing the difficulties involved in clustering the frontier points into sets is of interest.

In this paper, we consider a single robot in a bounded environment whose layout is unknown. We will focus on the details of implementation of a method that can circumvent many difficulties that arise when using frontier based methods in practice. In implementation of frontier based methods, no matter what criteria is used one needs to first cluster the point cloud of frontier cells and then choose one cluster as the sub-goal of navigation. Usually the centroid of the cluster is set as the next goal. However the clustering of frontier cells involves setting thresholds and tuning parameters based on the environment conditions and sensor parameters. The need for tuning put constraints on the applicability of these methods in practice. Even if the clustering problem is solved, the problem of tuning thresholds remains in selection stage.

We aim to propose a more general method that has the least dependency on parameter tuning. At the same time we want to take advantage of a global optimization with low computational cost.

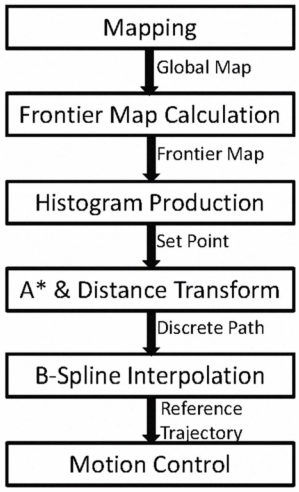

Figure 1. Block diagram of the proposed exploration technique.

II. Problem Definition and Assumptions

Suppose a single robot with a Laser Range Finder being mounted on it, situated in an *a priori* unknown unstructured indoor environment. The aim is to incrementally creating a map of the environment while exploring it until no unknown area remains. We seek to take the most advantage of the map and find the safest and shortest way for robot navigation throughout exploration.

Occupancy grid mapping is adopted for map representation because it takes no assumption about the structure of the robot surrounding and accounts for the sensor as well as robot motion uncertainties through using results from probability theory. Consequently, it is well suited for maintaining the map of unstructured environments. In addition, occupancy grid maps are able to maintain full information regarding free, unexplored and occupied areas in the map.

The framework of frontier exploration is taken as the basis framework (see [1]) and we seek to find a computationally low cost and reliable method to choose sub goals for exploration task. Paths toward sub goals has to be determined in the grid map. These paths generally have discrete nature with sharp corners which make them hard to follow from the control theoretic point of view. Supposing a constant translational velocity for the robot, the discrete path is required to be converted to a reference trajectory suitable for control purposes. In order to achieve this appropriate smoothing and sub sampling methods should be utilized.

In the next section our proposed method is explained based on these assumptions and criteria.

III. Proposed method

In this section we will briefly describe different steps of the proposed exploration method. These steps are summarized in the diagram of fig.1. The Laser Range Finder (LRF) sensor onboard the robot regularly scans the horizontal slice of its surrounding.

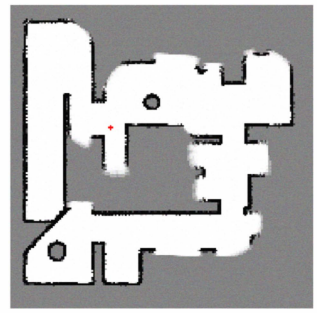

Figure 2. Occupancy Grid Map. Probability of occupancy for each cell is represented with colors ranging from white,representing free space, to black, representing blocked space.

Figure 3. Global Frontier Map in which white cells define frontiers between known and unknown areas

A. Mapping

Among the many map representation methods, occupancy grid maps are well suited for unstructured environments as they take no assumption about the structure of the robot surrounding and account for the sensor as well as robot motion uncertainties. Also, there exist efficient SLAM methods for incrementally constructing the map of the environment as the robot moves (e.g. [16], [17]). We, therefore, adopt Grid SLAM [16] as our mapping and localization algorithm. Grid map is maintained as a matrix of probabilities of occupancy of grid cells and each grid cell in the map is equivalent to a $d \times d$ square in real world. The grid map contains the information that the robot has gathered during its exploration so far and is used as the input in frontier calculation and path planning modules of the algorithm.

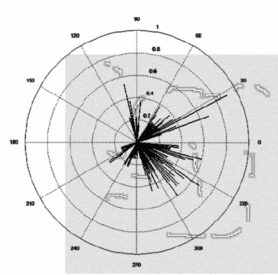

Figure 4. Global Frontier Map in which white cells define frontiers between known and unknown areas

B. Histogram Calculation

In each cycle of the algorithm, for exploration purposes, the robot needs to choose a set point as a sub-goal and find the most reliable and simultaneously shortest possible path from the robot's current position to the calculated set point. Following the idea of frontier exploration, we first extract the frontiers from the grid-map. Note that the grid map is of probabilistic essence and therefore one can categorize grid cells into three sets, namely obstacles, free cells and unknown cells, based on predetermined occupancy intervals. After this categorization, frontier cells are defined as unknown cells adjacent to free cells and this way a global frontier map can be produced like fig. 3 which is the frontier map related to the grid-map of fig. 2. In practice, the global frontier map consists of several point clouds that makes it hard to determine the sub-goals for exploration. In addition, the policy of choosing the centroid of the nearest frontier subset as the set point, apart from the difficulties its calculation involves, generally results in non optimal and crossed paths [12]. To circumvent these problems, we propose to use a histogram based method as follows.

First, all points in the global frontier map are transformed to the robot's current coordinate frame as shown in fig. 4. Then, polar histogram of these points is calculated with $\Delta\theta$ angle resolution in which the associated height of each bin is equal to the number of frontier pixels located in that bin's area. This results in a polar histogram like what is shown in fig. 5(a).

After this part two modifications will be applied to the histogram in order to prevent unnecessary calculations and parameter tuning otherwise would have been needed. The modifications consist of first normalizing the resulted histogram to the $[0, 1]$ interval and subsequently smoothing the resulted histogram by convolving it with a digitized $1d$ Gaussian function. During smoothing, the amount of each sector will be changed regarding to its neighbor's amounts i.e. the amount of small value sectors located between two great values will be increased and similarly the amount of a great value sector located between two smaller ones will be decreased. This will help converging several small subsets to a bigger one and consequently avoiding unnecessary calculations in later steps. An example of applying these modifications is shown in fig. 5(b).

After smoothing and normalizing, climax sets are determined as distinct subsets of histogram bins which have heights greater than a predefined threshold value, t_h. This way, as depicted in fig. 5(c), several climaxes are extracted from the modified histogram, among which the candidate for next exploration subgoal has to be selected. In the original frontier exploration paradigm, closest set is always become selected. This wisdom may sometimes avoid the robot from choosing the somewhat farther but greater frontier that has more information value in the presence of the closer but smaller frontier. It is reasonable then to have a compromise between nearness factor and the number of frontier pixels in choosing the best climax. Such a compromise could give the explorer a sense of global optimization. We perform this compromise in the following way.

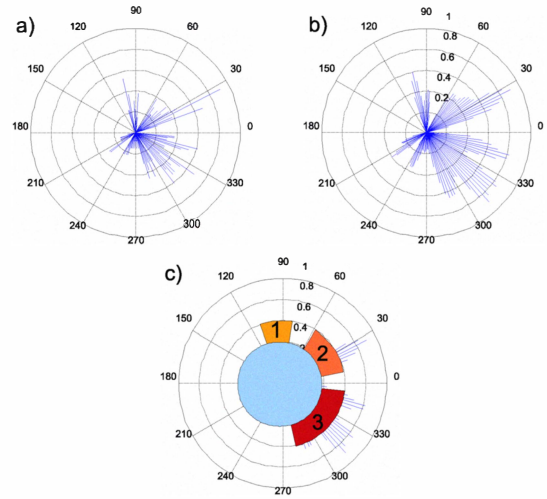

Figure 5. (a) Original histogram obtained from the map data, (b) Smoothed and normalized histogram, (c) extracted climaxes after applying the threshold to the histogram

For each climax the number of frontier cells is calculated and the relative distance between robot current position and the centroid of the climax is also obtained using A* [18]. These numbers are saved in two sets and then become normalized to the $[0, 1]$ interval by dividing each number to the biggest number of each set. Finally, score of each climax set,i , is calculated as follows in which s_i, d_i and c_i are representatives for score, normalized distance and cardinality of the climax set respectively. Ω and Θ are tuning parameters which balance between the importance of nearness and cardinality. Please note that these tuning parameters are not considered as limitations of our method. On the contrary, they provide flexibility in the sense that by adjusting them we can favor each criterion accordingly in the process of choosing the next best frontier.

$$s_i = \Omega \frac{1}{d_i} + \Theta c_i. \tag{1}$$

At the end, the best climax is selected as the one with the highest score among others and next sub-goal is set as the centroid of this climax. In the case that separated and unrelated frontiers exist in the best climax, the centroid of the nearest frontier will be selected as the sub-goal. Next step is finding a path through the unoccupied cells to reach this point.

C. Path Calculation

It is now needed to define the shortest and most reliable path from the current position of the robot to the set point calculated in the previous stage. It is also needed to consider the size of the robot in order to take a sufficient distance from obstacles. We account for these issues by using a combination of A* search algorithm and image distance transform.

Distance Transform is a derived representation of a digital image which labels each pixel of the image with a number proportional to the distance to the nearest obstacle pixel.

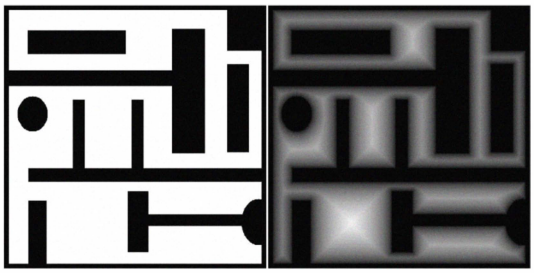

Figure 6. Distance Transform: the original image in the left side and the image after applying the distance transform in the right side

Consider for example the left image of fig. 6 as a map in which obstacle cells are marked with black and free cells with white. After applying distance transform to this map, the result would be a gray map image like the right side of fig. 6 in which the gray level of each pixel corresponds to the cost of navigating the robot through it. Map cells near to the obstacles will have higher cost, represented with dark gray, and the farther ones will have lower cost represented with light gray. Now, this cost map can be fed into the A* algorithm in order to find the path with the lowest cost which in our case means the shortest and most reliable path from the robot to the set point. A* algorithm (pronounced A-star) is one of the most popular search algorithms for path finding in grid-based maps which relies on the principle of best-first search [18]. However, in practice, the A* generated path cannot be used on its own for robot navigation due to the fact that it usually contains sharp turns which jeopardizes the stability of the robot motion from control theoretic point of view [15]. In fact, considering the scale of the map the discrete path yielded by A* needs to be downsampled, smoothed and converted to a trajectory before feeding into the robot motion controller. As it will be explained in the next section B-spline approximation is aided to achieve this goal.

D. Trajectory Generation and Control

1) Trajectory Generation: Reference trajectory is defined as the set of desired postures for robot motion along with their associated time stamps. In other words, the trajectory $s(t) = \{x(t), y(t), \theta(t)\}$ determines the motion profile of the robot in terms of its position, (x, y), and orientation, θ, as a function of time. In addition, generally, environmental, optimal and dynamical constraints are taken into account when determining the reference trajectory. Currently, for different purposes and applications, there exists some invaluable research work that can be refereed to and used (e.g see [19]); however, for our case, which is a differentially driven mobile robot in indoor environment with ramps and uneven surface, we adopted a simple and though efficient method based on B-spline approximation that can be used in most of the search and rescue applications. The details of our method are not explained here due to lack of space.

2) Control: The controller choice is affected by the robot hardware and software. In case of a differentially driven mobile robot, a reliable method has been proposed in [19] that is used in our implementation with slight modifications.

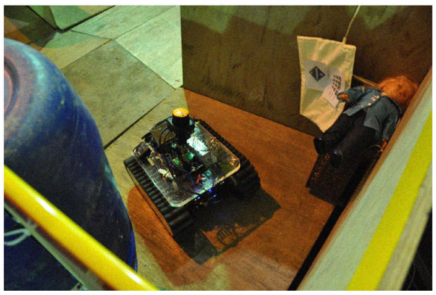

Figure 7. Melon, mobile robot that is used in the experiments. A UHG-08LX Hokuyo LRF is mounted on a stabilizer and both on the robot. Stabilizer aligns the LRF with respect to the same horizontal direction during the robot navigation.

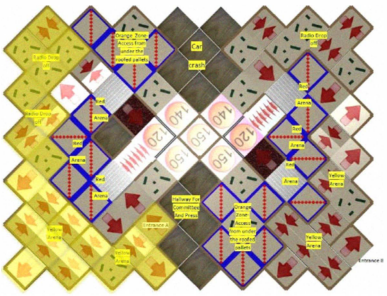

Figure 8. Ground truth map of the Iran Open 2010 rescue league. The robot was given the task of exploring the yellow area marked in the map. The area surface consists of ramps and palettes with small wooden obstacles

IV. Experimental Results

The performance of the proposed method is considered in this section via using it in both simulated and real exploration scenarios.

a) Real Scenario: We implemented our method on Melon, the mobile robot in our lab, which is shown in fig. 7. Mellon is equipped with a UHG-08LX Hokuyo LRF with a maximum of 8 meters range measurement and 270 degrees field of view. The LRF is mounted on a stabilizer that always holds its field of view aligned with the earth horizon. Usage of stabilizer allows for reliable navigation and mapping in environments with uneven and ramped surfaces since the LRF always scans the environment parallel to one horizontal line. In our experiment we put the robot in the yellow arena of 2010 Iran open rescue league with $28.8m^2$ area. The ground truth map is depicted in fig. 8. The goal is to explore the yellow arena of this region.

The generated map and the path traversed by the robot are shown in fig. 9. During the experiment, the robot was able to navigate the environment through a smooth path while keeping a reliable distance from the environment boundaries which are marked with black in the map. This is the result of using distance transform for generating the cost map of path generator. It appears from the fig. 9 that the robot explored the environment with approximately shortest and safest possible path. This experiment shows that our method can be applied in real situations in which robot do not necessary navigate on flat surface.

b) Simulation 1: In order to make comparative study and evaluate the exploration algorithm quantitatively we also ex-

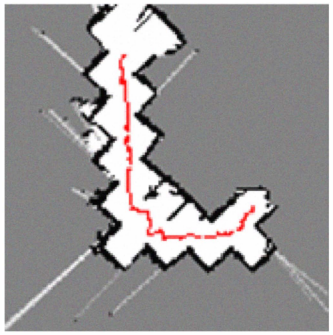

Figure 9. Generated map of the yellow area along with the path that the robot traversed in order to cover the whole area. Path is shown in red color within the white free area enclosed by the black walls and unknown gray area.

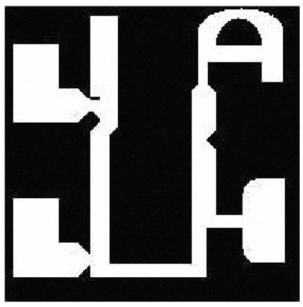

Figure 10. Simulated environment used to compare the performance of the original frontier exploration method vs. the proposed method

amined our implementation in a bigger $18m \times 18m$ simulated environment containing a more complicated map which is shown in fig. 10. The total area to be explored is $103.1m^2$ and the exploration mission is carried out using both the original and the proposed frontier exploration methods. Both methods were tested on the same map with identical assumptions about the kinematic and dynamic models and constants of the robot. The number of steps needed to completely cover the whole map is saved along with percentage of explored areas of the map per each step of robot movement. These are summarized in fig. 11 for both methods. Given that the path length traversed by the robot in each step equals $0.1m$ and is the same for all steps, in each case the total number of steps for mission completion is an indication of total path traversed by the robot

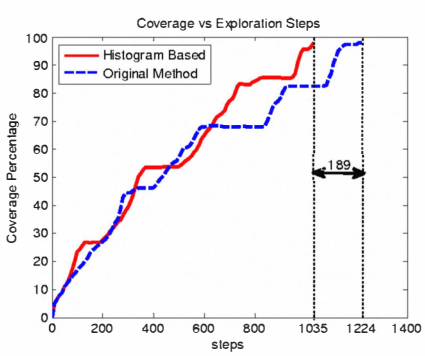

Figure 11. Comparison of original and proposed (Histogram Based) frontier exploration methods on the same map. The diagram shows the percentage of the explored area with respect to motion steps for each method.

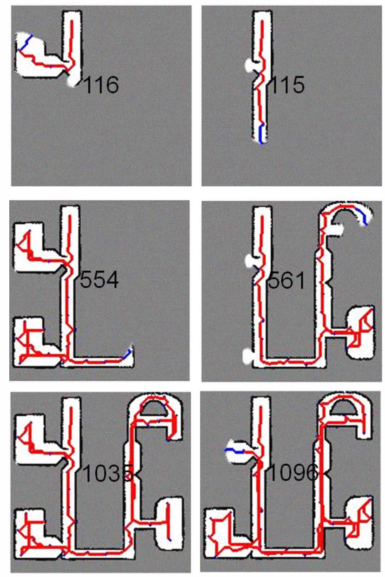

Figure 12. Comparison of the performance of Histogram Based method (left) with the original method (right). Each map is drawn with its associated step to show the progress of both algorithms along the time. The path traversed by the robot so far is also shown in red. As can be seen in the first and the second row, considering only the nearness factor causes the robot to ignore exploring the room like area in the right hand side of it. This does not happen if we consider also the cardinality of frontier sets in sub goal selection (see the left column).

during the exploration. As it can be seen from fig. 11 adopting our method, the robot was able to completely cover the map in 189 steps less than the original method which only considers the nearness factor for sub goal selection. In our experiment it means exploration of a $103.1m^2$ area with a path $18.9m$ shorter compared to the original method.

The source of this superiority can be understood by referring to fig. 12 in which the explored map is shown at some certain steps for both methods. The first row shows that considering only the nearness factor causes the robot to neglect the farther but greater frontier in favor of the closer and smaller frontier. This also happens in step 561 for the original paradigm of frontier exploration. As a result, using the original method, the robot needs to come back later to these critical points and explore the ignored areas while at the same time, by applying the proposed method, the robot could have completed its mission (see third row of fig. 12). Such superiority is mainly the result of considering both the cardinality and nearness of the frontier sets in choice of exploration sub goals. Therefore, it can be concluded that introducing the new mixed criteria for choosing the candidate frontier set can improve the performance of the exploration from path length point of view at list in some certain cases.

c) Simulation 2: In order to evaluate the general performance of our algorithm we tested it in different simulated environments and by putting the robot on random locations in these environments. We also compared the results of our algorithm against the results obtained from original method of [1]. No effort has been made to make favorable maps for our algorithm and all related constants are assumed to be the same for both methods like the previous experiment. Maps

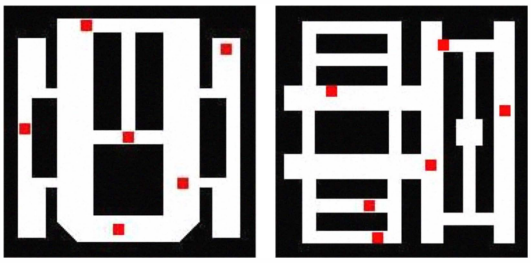

Figure 13. Maps that are used for comparing the general performance of original frontier exploration method against our method. Random starting points are marked using red squares

left map	1	2	3	4	5	6
proposed method	1215	1375	1301	1287	1486	1516
original method	1208	1489	1562	1542	1705	1541
right map	1	2	3	4	5	6
proposed method	1563	1632	1662	1454	1477	1705
original method	1741	1632	1541	1540	1619	1568

Table I
PERFORMANCE COMPARISON FOR THE LEFT MAP AND THE RIGHT MAP OF FIG. 13.

that are used for the comparison are illustrated in fig. 13 along with 6 randomly generated starting points for robot exploration marked by red squares.

Number of steps for complete coverage of the map is reported in tab. I. For the left map of fig. 13 according to tab. I in 5 out of 6 cases our proposed method outperforms the original frontier exploration method and in one case it has a close performance. For the right map of fig. 13 according to tab. I, in 4 out of 6 cases our proposed method outperforms the original frontier exploration method.

V. CONCLUSION

The research work presented in this paper introduces a novel criteria for selecting sub goals for frontier based exploration. It benefits from a simple but efficient philosophy that both closeness and cardinality should be taken into account in order to improve the performance of the original paradigm of frontier exploration. The method is simple to implement and needs low computational cost. The idea of using histogram calculations to gather information about frontiers also extricates us from most of the complexities and parameter tunings that arise dealing with grid maps in practice.

It should be noted that since in exploration problem the environment is *a priori unknown,* no real optimal strategy could be offered. However, suggested by the above experiments, our proposed method overall outperforms the original frontier based exploration while it has the additional flexibility and simplicity of implementation. Referring to (1), also, it can be argued that the new criteria adds a sense of global search for the best frontier to the exploration algorithm. One can adjust the algorithm coefficients in order to put more emphasize on local or global search, where by local we mean searching for the closest frontier set and by global we mean searching for the greatest one. In fact it is even possible to change the balance between nearness and cardinality coefficients during the navigation. This provides the opportunity to use other optimizations and may be learning techniques to adapt algorithm's constants which consequently expands its application. Finally, the simplicity and low computational cost of implementation along with flexibility of use and extendability of the proposed method makes it suitable for real world applications.

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