A Framed-quadtree based on Reversed D* Path Planning Approach for Intelligent Mobile Robot

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***Abstract*—This paper proposes a new path planning system combining framed-quadtree representation with the reversed D* algorithm to improve the efficiency of path planning. The utilization of framed-quadtree representation is for improving the decomposed efficiency of the environment and maintaining the representation capability of maps. And the feature of reversed D* algorithm is that it does not need to calculate the value of the goal distance. The core of reversed D* algorithm is to use the "robot distance" to establish the local potential field, which realizes dynamic optimization by the way of search "escaping point" as the middle goal location. The theoretical analyzing and studying simulation results to the proposed method demonstrate that the proposed path planning system has potential.**

***Index Terms*—IMR, framed-quadtree, reversed D*, work space**

I. INTRODUCTION

An intelligent mobile robot(IMR) is a robot system, including environment perception, decision-making, planning, motion controlling [1], which can move autonomously in the environment including obstacles and achieve scheduled tasks, acquiring the environmental information though the sensors. The topic of navigation is one of the focused points in the correlation technique of IMR. Path planning is an essential aspect of the research for navigational technique. The task of path planning is to guide the robot towards the goal point without a collision with obstacles. Path planning is process which a mobile robot can seek a motion path which is an optimal or approximately optimal from initial state to target state. According to integrated degree of environmental information, path planning approach could be classified into: global planning and local planning.

Global path planning is usually used in a completely known environment.There are two classic approaches: occupancy grid approach and topological maps approach.The occupancy grid approach was first proposed by Hans P. Moravec and Alberto Elfes [2].In recent years, Soon Mook Jeong el at use sonar to built the grid map which represents the robot's surroundings to solve local minimum problem [3]. Probability grid arrangement which combines Bayesian probability with grid map-building is presented in [4]. There are other improved grid methods in [5-6].The topological maps approach is a purely geometrical approach, which concludes nodes that means distinguishable different places or robotic states and links which means the relation between the nodes. Tae-Bum [7] proposed a thinning-based topological exploration (TTE) based on the position probability of the end nodes of a topological map from a binary grid map. Another improved approach is Navigable Voronoi Diagram (NVD) [8], in which proposes the cost function to calculate next heading direction of the robot. The other approaches are in [9-11].

The local path planning approach is more efficient in IMR navigation in real application when the environmental information is totally unknown or only partially known. The classic methods are Dynamic Window Approach and Potential Field method. In 1999, Oliver Brock proposed the global dynamic window approach [13] which combines real-time obstacle avoidance and motion-based planning to allow a mobile robot to navigate safely and at high speeds to reach a goal position without prior knowledge of the environment. [14-15] show some improvement of dynamic window approach. Potential field method (PFM) is first proposed by Khatib [16] and has been widely used in obstacle avoidance cases [17-20].

IMR navigation means a robot has the ability to decide how to travel through a given environment. A robot and obstacles both exist in the navigation called the "work space". A good or feasible path from the starting to the target implies that IMR avoids collisions with obstacles. The purpose of path planning is to generate and optimize a good or feasible according to the current environment. This paper proposes a new path planning system combining a framed-quadtree to represent the "work space" for improving the decomposed efficiency of the avoidance and motion-based planning to allow a mobile robot to navigate safely and at high speeds to reach a goal position without prior knowledge of the environment.

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The paper is organized as follows: Section II is "work space" of IMR navigation which introduces some related concepts to the quadtree and framed-quadtree representation. The core and principle of the reversed D^* algorithm is discussed in section III and the followed is simulation results in section IV. Finally, conclusions are discussed in the last section V.

II. "WORK SPACE" OF IMR NAVIGATION

A quadtree representation is presented for path planning by Subbarao Kambhampati et al. in 1986. A quadtree representation is a tree whose leaves represent square areas or quadrants of the image. Compared to the grid representation, the quadtree representation divides the same size of region into blocks, and each part of the local classified division in accordance with the characteristics of region. Fig. 1 is the environment with an obstacle. Fig. 2 is the grid decomposition representation of Fig. 1. The quadtree decomposition representation of Fig. 1 is showed in Fig. 3.

A quadtree is a recursive decomposition of a two-dimensional picture into uniformly colored blocks. They are labeled with the color of the corresponding area, black, white, and gray. Quadtrees can be stored as lists of all nodes' records or locational codes. A node of a quadtree represents a $2^n \times 2^n$ square region of the picture which is work space of IMR. The grid cells could be empty so that IMR can visit them or the grid cells could be occupied as an obstacle. A white node in the tree means a region of free space. A black node means there is the region of obstacles. And a gray node is the node representing a region having a mixture of free space and obstacles. By the other means, the gray node is the node which can be decomposed.

The decomposition process of the quadtree representation has two parts. Firstly, the tree structure shows the location and size of each homogeneous region. Secondly, the cell value is specified at each sub-node (leaf node) of the tree that means which is an obstacle, visited space or unvisited space. A quadtree leaf node is a tip node of the tree. The whole image or work space is recursively subdivided until either a sub-region free of mixtures is found or the smallest grid cell (minimum resolution) is reached.

In addition, the relation between size of block and viability of the block is a negative relation, contributes to improvement of the efficiency of quadtree segmentation. Based on the feature of a quadtree representation, it efficiently partitions the environment which is represented nodes.

Framed-quadtree which combines together the accuracy of high resolution grid-based path planning techniques with the efficiency of quadtree-based techniques is presented as a modified data structure [21]. In this paper, the framed-quadtree representation algorithm (FQR) is used for decomposing the environment into rectangular blocks of similar value cells.

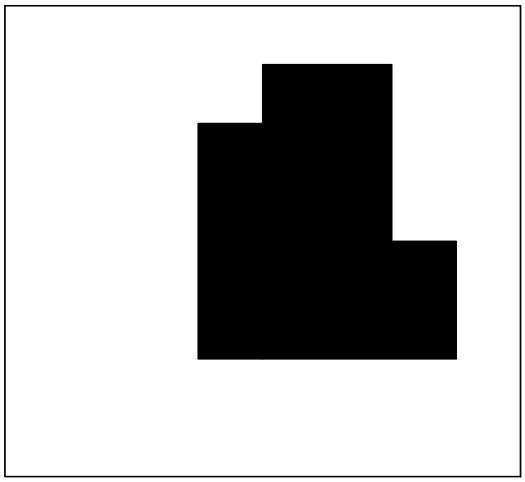

Figure1. the environment with an obstacle

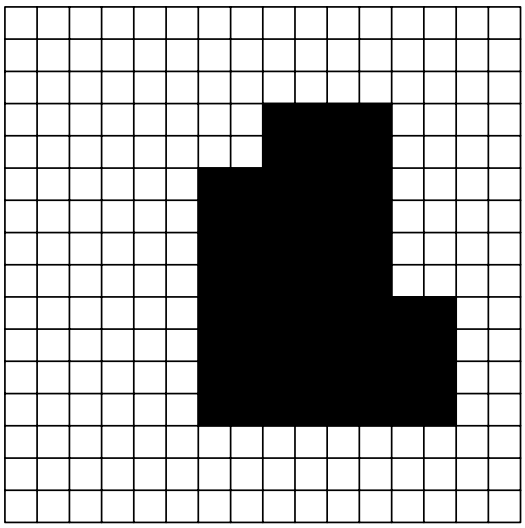

Figure2. the grid decomposition representation

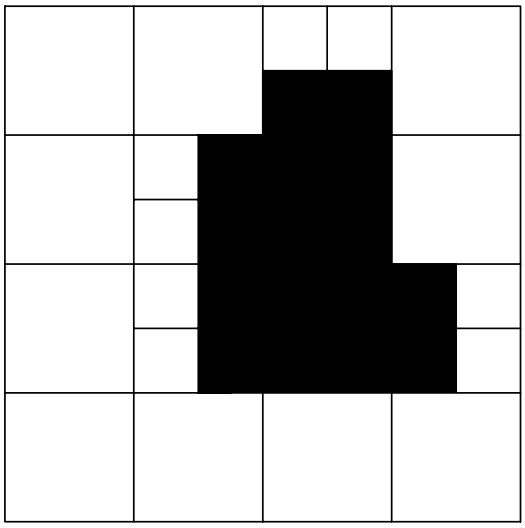

Figure3. the quadtree decomposition representation of Figure1

The FQR allows accurately searching each individual f-quad (regardless of its size) in linear time with respect to the perimeter of the f-quad. Furthermore, it is not

sensitive to obstacle placement near quad boundaries and will generate a shortest paths based on the metric. The coding approach of FQR is showed in Fig.4. According to the coding approach, Fig.5 shows the coding results of Fig.3. In Fig.5, the root node is 0, the other nodes are:

Glay node: 1, 2, 3, 4, 7, 9,
12, 13, 14, 18,
White node: 5, 6, 8, 10, 11, 15,
16, 17, 19, 20, 21,
24, 25, 26, 38, 39,
41, 44
Black node: 12, 13, 22, 23, 27,
28, 37, 40, 42, 43

III. PATH PLANNING USING REVERSED D*

A. A* and D* algorithm

Another classic approach in the local environment based on the partial information is A* search which came from Dijkstra algorithm. Stentz presented two developed algorithm: D*(Dynamic A*) and Focussed D*. D* and Focused D* methods have been developed to accelerate the re-planning process. These methods are called Dynamic A* Method, however, only the second one allows us to use the heuristic cost function in reality. In recent years, researchers presented lots of improved heuristic search approach which are Differential A* algorithm [22], Focussed Dynamic A* Lite (D* Lite) [23], hierarchical D* algorithm [24], Anytime D* algorithm [25].

A* search (in Fig.6) needs two parts of information about each node of the graph: g (n) is the cost of the best path from the start point to any search node n. And h (n) is the heuristic function which is an estimate of the cost from any node n to the goal according to some expectation. The search procedure expands nodes in order of increasing expected cost or evaluation function f (n) which is a combination of the g (n) and the h (n):

$$f(n) = g(n) + h(n) \qquad (1)$$

Usually, robots fine the best path in the decreasing direction of h (n).

The D* algorithm is a dynamic version of the A* algorithm. A* algorithms is widely used in off-line path planning. However, the D* is path length optimal algorithm and saves a lot of computational time when the robot meets the obstacles. D* algorithm restarts the general search process of an A* algorithm when an obstacle is detected. During the time of moving to the goal point, IMR plans a new path to getting a "broken" point for escaping the dynamic obstacles when IMR meet the dynamic obstacles. Then IMR recover the initial planning path to the goal point after IMR escapes the dynamic obstacles following the converted path. In Fig.7, there is a new obstacle in the initial planning path when

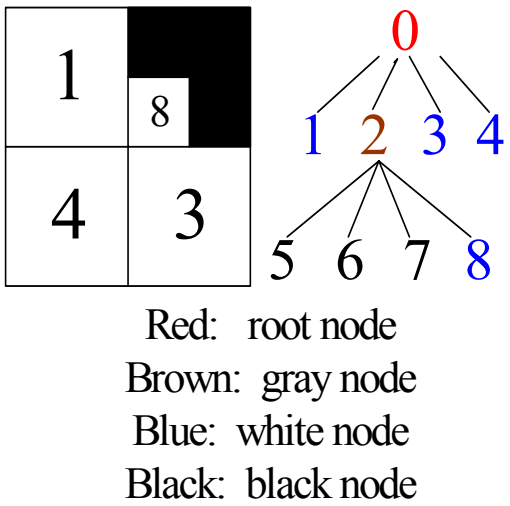

Figure4. the coding approach of FQR

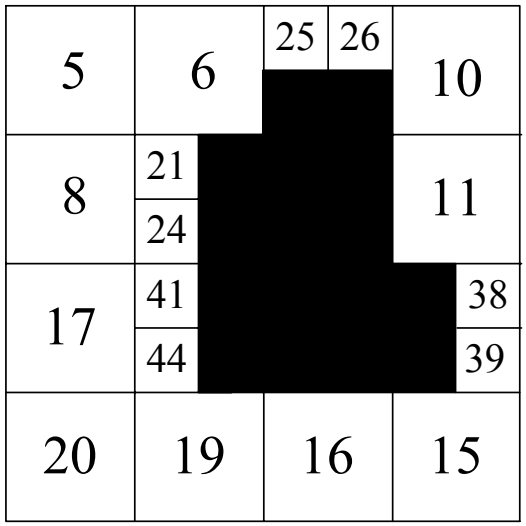

Figure5. the coding results of Figure3

IMR reach the M point. IMR re-plans a new path from M to the middle goal K (the goal point value of K is less than M) based on the A* algorithm. The D* algorithm allows optimality and special lower computational time. However, there are lots of difficulties using the D* algorithm when the environment is large or the integrated degree of environmental information is party.

B. Reversed D* algorithm

D* algorithm is used based on the most known environment information. In the unknown environment, IMR only acquires the condition of around environment partly. In the case of unknown the condition around environment of final goal point, there are unavoidable deviation between the model of distance from the start point to the goal point based on A* algorithm and the real work space. D* algorithm is available in the condition of small environment and is unavailable in the large space.

This paper uses the reversed D* algorithm [26] which no more calculates the value of the goal distance than utilizes the definition of "robot distance" to establish the

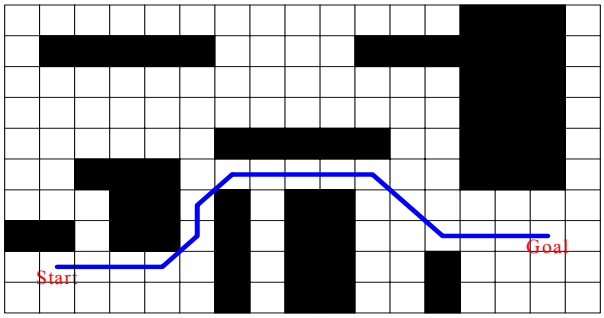

Figure6. A* search

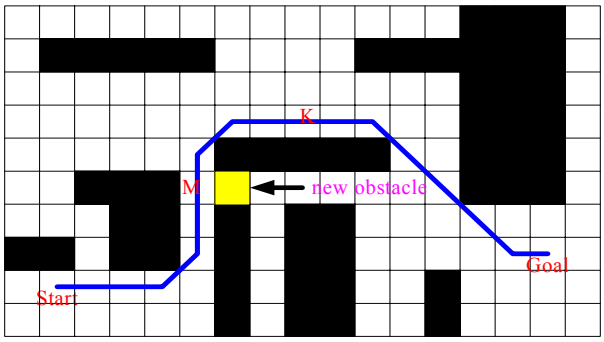

Figure7. D* algorithm

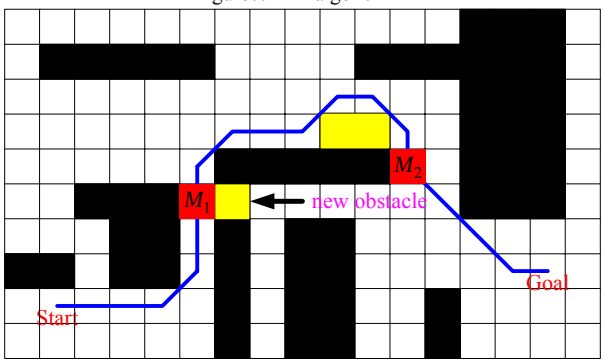

Figure8. reversed D* algorithm

local potential field with the center of robot current location. It realizes dynamic optimization by the way of search "escaping point" as the middle or temporary goal location. The process of reversed D* algorithm is shown in Fig.8. The principle of D* algorithm is as followed:

(1) It is supposed that $F_{\min}$ is the minimal value of goal potential field during the moving process from the start point $Start(x_s, y_s)$ to the goal node $Goal(x_g, y_g)$. The goal potential field function of coordinate (x_i, y_i) is

$$F(i) = \sqrt{(x_i - x_g)^2 + (y_i - y_g)^2} \qquad (2)$$

During the dynamic optimization, IMR expands to search the "escaping point" whose goal potential field function is less than $F_{\min} - \varepsilon$, ($\varepsilon > 0$) as the center of the current location $R(x_c, y_c)$. The "escaping point" is labeled with $L_j(x_j, y_j)$, ε makes sure that the potential field function of $L_j(x_j, y_j)$ is less than $F_{\min}$. The "escaping point" $L_j(x_j, y_j)$ is the middle goal which makes (3) as the estimate of the cost during the moving to the final node point.

$$F(L_j) = \sqrt{(x_j - x_g)^2 + (y_j - y_g)^2} < F_{\min} - \varepsilon \qquad (3)$$

(2) A* algorithm is used to establish the estimate function during the searching the middle goal $L_j(x_j, y_j)$. According to the searched node (x_i, y_i), the estimate function is $f(i) = g(i) + h(i)$. It is different with D* algorithm that $g(i)$ is the real distance cost from current location $R(x_c, y_c)$ to the searched node (x_i, y_i), which is called "robot distance". $h(i)$ is the estimate of the cost from the searched node (x_i, y_i) to the goal node, then $h(i) = F(i)$.

(3) The "robot distance" $g(i)$ is labeled in the search space. We could backtrack current location $R(x_c, y_c)$ of IMR according to the reducing grade direction of $g(i)$ from $L_j(x_j, y_j)$ when IMR arrive at the middle goal $L_j(x_j, y_j)$ under the condition of the formula (3). The reversed process of backdate is the path from current location $R(x_c, y_c)$ of IMR to the middle goal $L_j(x_j, y_j)$.

In Fig.8, IMR realize the path planning from the Start node to the Goal node by three times dynamic planning. The first time, IMR finds the M_1 node as the middle node. IMR searches the M_2 node as the second middle node by another dynamic planning after it arrives at the M_1 node. IMR reaches the Goal node by the third dynamic planning after it arrives at the M_2 node.

Fig.8 shows that it could back-track current location $R(x_c, y_c)$ of IMR after arriving at the middle goal $L_j(x_j, y_j)$ according to the reducing grade direction of $g(i)$ from $L_j(x_j, y_j)$. The reversed process of backdate is called reversed D* algorithm. It no more establishes the initial goal distance potential field than realizes dynamic optimization by the way of search "escaping point" as the middle or temporary goal location.

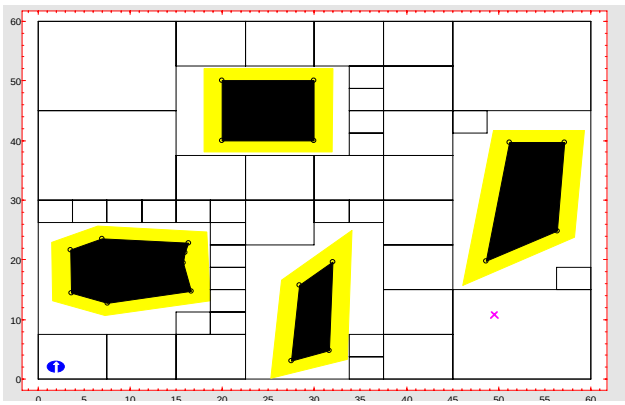

Figure9. "work space" divided by FQR is divided into lots of parts by FQR

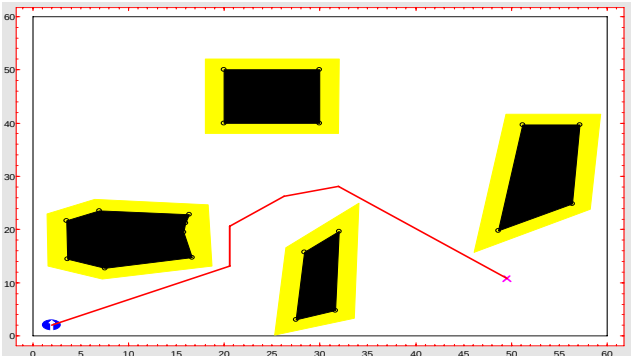

Figure10. the shortest path based on the reversed D* algorithm

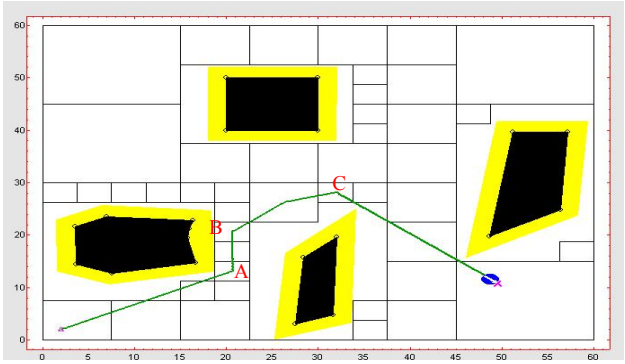

Figure11. the result of simulation based on FQR and the reversed D* algorithm

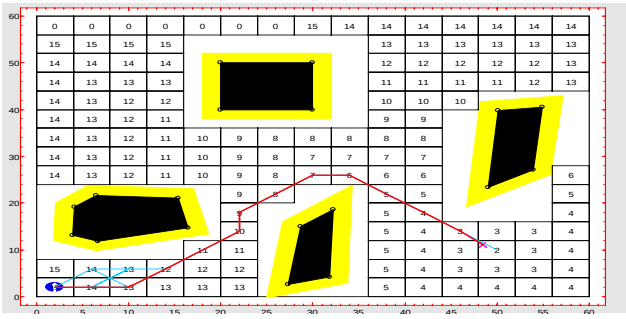

Figure12. the result of simulation based on grid decomposition and the D* algorithm

From Fig.7 and 8, it is similar to the search region of reversed D^* algorithm and D^* algorithm in the static environment. In the dynamic or unknown environment, reversed D^* algorithm search region in the outside direction as the center of IMR. It is dependable that IMR does not utilize the environmental information far away from it but updates the environmental information around itself based on the sensors.

. EXPERIMENTAL RESULTS

In the experiment, we use the simulation soft introduced in [27]. Fig.9 shows the environment of simulation. The "work space" is a 60*60 square region. The IMR moves toward the destination point from the start location using the reversed D* algorithm to search the optimal path. The IMR is regarded as a point and represented by a blue circle with one white arrow inside it and the destination point is represented by a X. The blue circle diameter is specified by the maximum robot dimension and the arrow shows the current orientation. The position of obstacles in "work space" is random and they are represented by random polygons with yellow and black colors. There are four polygons in the "work space". The result of divided "work space" by framed-quadtree representation is also showed in Fig.9.

The calculated shortest path based on the reversed D* algorithm is showed in Fig.10 and Fig.11 shows the final result of simulation. Initially, IMR attempts to go directly to the destination point but it perceives there is an region of obstacles in front and it has to come round it when it arrives at the point A. IMR replans the path from point A to point C passing point B based on the reversed D^* algorithm which means point B and point C are "escaping point" as the temporary goal location. IMR has past the region of obstacles totally when it arrives at the point C. Then it goes on moving toward the destination point and arrives to the goal finally. Fig.12 shows the result of simulation based on grid decomposition and the D* algorithm. It is demonstrated that the approach proposed in this paper is more effective by comparing Fig.11 and Fig.12.

V. CONCLUSION

This paper proposes an approach which combines framed-quadtree representation with the reversed D^* algorithm to improve the efficiency of path planning. The framed-quadtree is wonderful representation to improve the decomposed efficiency of the environment as the same time maintaining the representation capability of maps.

The reversed D^* algorithm is an improved version of D^* algorithm. The core of reversed D^* algorithm is to use the "robot distance" to establish the local potential field, which realizes dynamic optimization by the way of search "escaping point" as the middle goal location. The reversed D^* is shorter, simpler, and consequently easier to understand and extend than D* and is more efficient by the theoretical analyzing.

The result of simulation of our approach shows that IMR replans the path based on the reversed D^* algorithm when it perceives there is a region of obstacles in front and has to come round it, and the replanning path includes the two "escaping point" as the temporary goal location. By comparing with other approach, it demonstrates that the proposed path planning system is more effective and has enough potential. And we hope it could be realized in reality during our next work.

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