Mobile Robot Navigation using Multi-resolution Electrostatic Potential Field

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Abstract— **This paper proposes a multi-resolution electrostatic potential field (MREPF) based solution to the mobile robot path planning and collision avoidance problem in 2D dynamic environment. The MREPF is an efficient method in calculation time and updating field map. The large scale resolution map is added to EPF and this resolution map interacts with the small scale resolution map to find an optimal solution in real time. This approach can be interpreted with Atlantis model. The simulation studies show the efficiency of the proposed algorithm.**

Keywords— **mobile robot navigation, path planning, multi-resolution, potential field, Collision avoidance.**

I. Introduction

Building autonomous robots has been an important objective of the research in artificial intelligence and robotics. Specially in mobile robot research area, the autonomous navigation has been developed by many researchers [1], [2], [3], [4], [5], [6], [8]. There are three stages on this subject-mapping, localization and control. Mapping is a map-building method from range data such as laser finder or ultrasonic sensors. Localization is to know where the robot is from the mapping and dead-reckoning sensor and other data. Recently the simultaneous localization and map building(SLAM) methods are used to get mapping and localization simultaneously. After localization and mapping, the robot has to have control method. This is a path-planning algorithm that is an important issues because the environments are dynamics and the robots cannot see the entire environment[7].

In this paper, the path-planning method is proposed for navigation that is cooperating with appropriate mapping and localization methods. To cooperate noisy sensor data, we use the occupancy grid method that is popular because it is simple and stochastic algorithm[2]. This method is relatively robust for noisy sonar data because it updates the posteriors with gaussian process. For the path-planning and navigation, potential field method was suggested by Khatib and Krogh. This method generates a field representing a navigational space based on an arbitrary potential function. The classic function used is that of Coulomb's electrostatic attraction. Recently different type(circuit analogy) of potential field was developed as the name of EPF.

The Electrostatic Potential Field(EPF) based solution to the mobile robot path planning and collision avoidance problem in 2D dynamic environments is previous researched[3], [4]. This paper is the extension of that work - the multi resolution approach. The EPF is obtained in four steps - first creating an occupancy map of the environment, second creating the corresponding resistor network that is representative of the mobile robot's operational environment, third creating the conductance map from the resistor network and finally solving the resistor network to obtain the potential field. In EPF, the laws of electrostatic fields are used to prove that the approach generates a minimum occupancy approximately optimal path. To calculate an optimal path, this method examine overall path from current position to goal. The EPF algorithm is as efficient as the dynamic programming but to calculate and update the effective cost of the remainder of the path require all information about resistance map. When the current position or goal position is changed, EPF algorithm must calculate for all nodes.

The Multi-Resolution Electrostatic Potential Field (MREPF) is an efficient EPF accelerating calculation time and updating field map efficiently. In EPF, there is trade-off relation between calculation time and accuracy. The calculation time increases as grid size decreases and the accuracy increases as grid size decreases. Therefore, it takes loss of time to get more optimal path. The MREPF is a solution for this trade-off problem. As previously mentioned, the MREPF is more efficient than EPF in calculation time and updating data. The large scale resolution map is added to EPF and this resolution map interacts with the small scale resolution map to find an optimal solution in real time. When mobile robot navigates, only large scale resolution map that includes the corresponding small scale resolution map is updated. The large scale resolution maps provide robot a rough path to goal, then the robot calculates the path to next large scale cell in small scale resolution map that can be determined by sensor data. This approach can be interpreted with ATLANTIS model. The large scale resolution map directs next goal as sequencer do. The small scale resolution map calculates current motion vector as behavior layer do.

A comprehensive study of the problem and a survey of techniques used for planning is given in [3], while a long list of additional references is given in [4] and [8]. The EPF related methods are used to solve navigation problems.

The rest of paper is organized as follows. In chapter 2, the proposed method of solution will be explained. The EPF method is first briefly reviewed and then the multi-resolution approach will be described. In chapter 3, The simulation results are showed to prove the proposed method. Finally in chapter 4, we conclude the paper.

II. Proposed Method of Solution

The EPF is well described in the previous research. here, we review the concept of EPF briefly. The EPF solution to the navigation problem is compared to the flow of electric current within a sheet of conducting material; The environment and obstacles are mapped into a discrete electric circuits(resistance). The point is the path of minimum resistance with in circuit maps into a path of minimum occupancy within the environment. In the occupancy map, each cell is replaced by a resistor network. The value of the resistors is determined by the value of the corresponding cell in the occupancy map.

Since maximum potential drop occurs on the minimum resistance path in the network, reversing the mapping generates an optimal path in the environment corresponding to a minimum occupancy path.

Once the occupancy map is generated, each cell is then mapped onto a resistor network by replacing each cell in the occupancy map with a set of eight resistors(N, NE, E, SE, S, SW, W, NW), each resistor connected at central point. The resistor network is obtained using the α-norm approach each resister is connected to one resistor from the eight neighboring cells. see the fig.1

Considering an environment, EPF model this environment a square gird, Let m by n grid. In the EPF method, this environment has to include the initial point q_0 and destination point q_f. The grid is discretely represented by the occupancy matrix O, where the value of each entry is the percentage of the area of the grid cell, occupied by obstacles of the environment map.

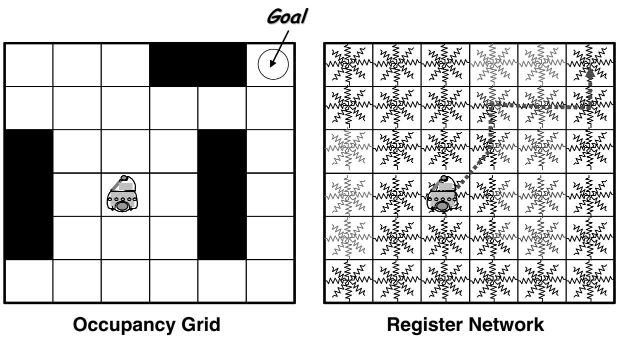

Fig. 1. EPF example.

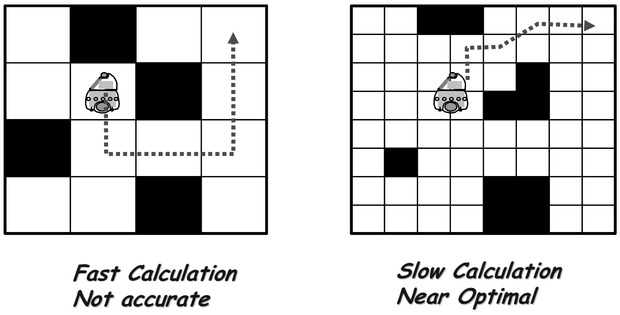

Fig. 2. The trade-off relationship of EPF.

In the EPF, to determine a desired direction of travel, a vector is associated with each cell connected to the cell containing q_0 with magnitude equal to the amount of current flowing through the specified branch. The sum of these vectors is then reported to be the direction of travel along the minimum occupancy path. In this approach, there is trade-off between speed and accuracy. Increasing the connectivity of the cells or reducing their size increase the accuracy of the generated path. In [3] the authors interpret EPF as follows; The criterion used for determining the path optimality is the total occupancy of the path swept by the robot as it follows the trajectories, or the total swept occupancy. Each square unit of area in the environment is assigned a minimum occupancy. Highly cluttered areas are assigned a larger occupancy value. This criterion for optimality is superior to a simple distance criterion when the algorithm is to be implemented in a real environment. A planned path, which minimizes distance, tends to drive the robot arbitrarily close to any obstacles between the robot and the goal point. Minimizing swept occupancy, the EPF path planner avoids the areas close to the object, which increase the total swept occupancy.

In EPF, there is trade-off relation between calculation time and accuracy. The calcuation time increases as grid size decreases and the accuracy increases as grid size decreases. Therefore, it takes loss of time to get more optimal path.

See the fig.2 The non-optimal path is generated in low resolution map, on the other hand The optimal path is generated in high resolution map. But for the calculation time, the low resolution map have the advantage comparing to high resolutio map.

In this paper, we try improve this trade-off characteristic of EPF with Multi-resolution technique.

Considering gird map that represents the occupancy of the environment and obstacles. In EPF the resistor network is generated on each cell and it represents the occupancy probability. To plan optimal path, for this network EPF algorithm is used. it is efficient full-search algorithm such as dynamic programming

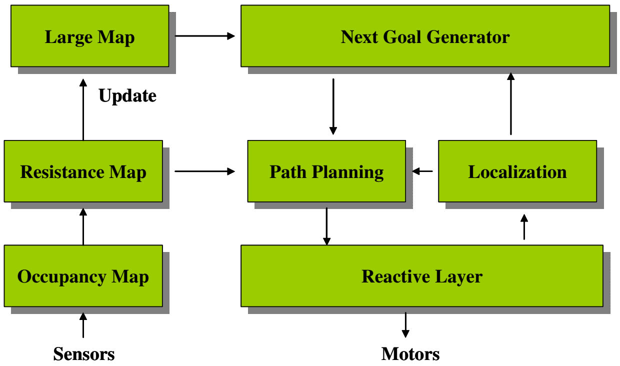

Fig. 3. The overall architecture.

If the environment changes, the EPF re-calculated on overall node of dynamic programming. Considering Atlantis model - it is a kind of behavior based architecture. In this model, the sequencer provides the next goal to behavior layer. Assuming this sequencer exists in EPF, the sequencer provides next goal to small EPF that containing current robot position and next goal. EPF calculate only small region that is within the sensing distance - the robot know the map information directly. In this case, the grid size can be small enough to get good accuracy. The main idea of this paper is implementing this sequencer layer with multi-resolution approach.

The rough path can be generated by rough map information. The exact path is only needed near robot because the robot moves in dynamic environment. To do this the large scale map is proposed. The large scale map containing the information of minimal path in the large grid. The eight resistors represent the large grid with the values that calculated based on small grid resistors.

$$\begin{aligned} R_N &= min\{occupancy(q_c, q_n)\}, \\ R_{NE} &= min\{occupancy(q_c, q_{ne})\}, \\ R_E &= min\{occupancy(q_c, q_e)\}, \\ R_{SE} &= min\{occupancy(q_c, q_{se})\}, \\ R_S &= min\{occupancy(q_c, q_s)\}, \\ R_{SW} &= min\{occupancy(q_c, q_{sw})\}, \\ R_W &= min\{occupancy(q_c, q_w)\}, \\ R_{NW} &= min\{occupancy(q_c, q_{nw})\}, \end{aligned} \tag{1}$$

If the value of the eight resistors is determined, the large scale map can determine a rough path that can provide the next goal to behavior layer that is implemented by EPF. The EPF algorithm is used to determine optimal rough path that is same as EPF. In fig.3 shows the overall architecture that explains the multi-resolution concept. the large map is updated based on resistance map that is made by sensor data. The next goal generator use large map to determine next goal by EPF algorithm for the nodes of large map. Mixing localization result, path planner solve the reactive input to navigate robot. The overall algorithm of Multi-resolution Electrostatic Potential Field model is as follows:

( ) From sensor data, get the occupancy grid.
( ) From occupancy grid, get the resistance map
( ) Update the large scale map that containing robot position
( ) Calculate the next goal for the robot based on large scale map
( ) Based on current region calculate the EPF from current position to next goal. When the environment is changed, go to step (3).

The Multiresolution concept is describe in Fig.4. For sensed high resolution map and outside low resolution map, calculate the optimal path and determine just next goal. If the robot reaches the next goal, the robot recalcuate the path. First time, the path is not optimal because the optimal path is blocked in the low resolution map. But the time the robot reaches the blocked region, robot can see the optimal path because the optimal path is open in the sensed high resolution map.

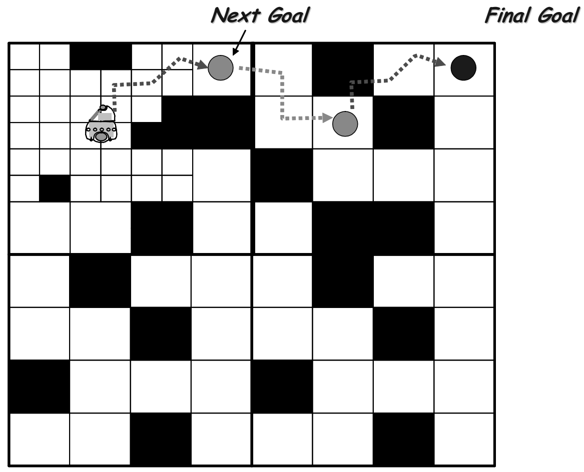

Fig. 4. The MREPF concept.

In the EPF the complexity of the total solution is the summation of the complexity of Cholesky factorization and single pass complexity and the complexity of finding the Cholesky factorization of the system matrix including sparsity of the system matrix and with previous knowledge of the created fill. So the complexity of the total solution is as follow:

$$\begin{aligned} C &= C_{OM} + C_{IM} + C_S \\ &= mn_M + m(4n_M + 1)size^2 + 3size^2 + size \end{aligned} \tag{2}$$

where, n_i is the number of vertices of the i-th polygon of the space, size is the dimension of the resistor network and m is the number of polygons in the space. and n_M is assigned to be the maximum number of vertices of any polygon in the space.

In MREPF, the complexity is reduced as the size is reduced. so the overall complexity of MREPF can be expressed using EPF complexity.

$$\begin{aligned} C &= C_{OM} + C_{IM} + C_S \\ &= mn_M + m(4n_M + 1)size_N^2 + 3size_N^2 + size_N \end{aligned} \tag{3}$$

where $size^N$ is the summation of sensed high resolution grid size and outside low resolution grid size.

III. Simulation and Discussion

In this paper, the robot that have two wheels and twelve sonar sensor is simulated. The environment is Visual C 6.0 in windows XP and Pentium 4 2.4Ghz. There are dead-reckoning error and sensor noise with Gaussian distribution. The sonar beam angle is 22.5 degree that of Polaroid 6000 series. fig.5 shows the simulator in this paper. the robot has sixteen sonar sensors that cover 360^o and dense front sensing. Following examples show the situation for static local minimum problem and dynamic environment examples. See the fig.6 and fig.7.

In the fig.6, the robot resolve the local minimum problem with grid map and path-planning. This result is almost same as the EPF. In the fig.7, the robot met the unknown object - centered one and move with another optimal path. These results show that the MREPF can navigate appropriately for static and dynamic environment as the EPF navigate the environments. We will discuss the difference from EPF in next section.

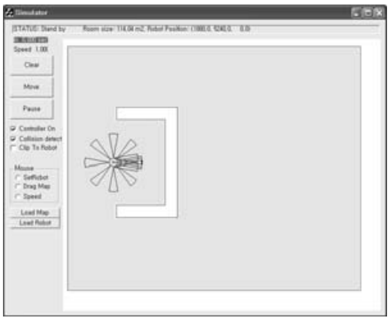

Fig. 5. simulator based on Visual C.

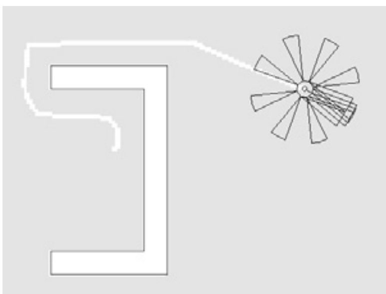

Fig. 6. Local minimum test : the robot plan the optimal path when the direct path is closed.

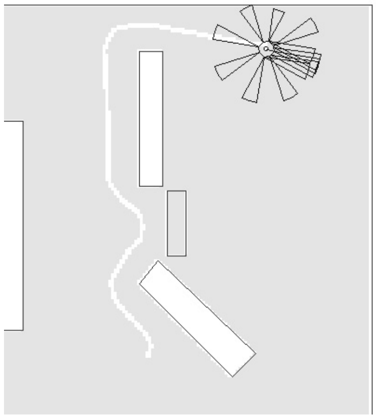

Fig. 7. Dynamic environment test : When the first path is closed by dynamic obstacle, the robot generate another path.

In the previous section, the results for MREPF is similar to EPF. The main advantage of MREPF is that the calculation time is smaller than EPF. The accuracy of EPF mainly depends on the grid size of occupancy map. If same gird size is used, the EPF is more safe than MREPF because MREPF generate the rough path for robot that is not the optimal plan but near optimal. But consider the trade-off relation in EPF. For the real-time operation, there are the limit of grid size that determine the accuracy of algorithm. In MREPF, the grid size can be smaller than EPF because the calculation time is smaller than EPF. In the EPF algorithm, The grid size used to calculate the EPF-based path was set to be 20×20 giving a sampling rate of approximately 2.13s. (Note that a grid size of 10×10 reduces the sampling rate to approximately 0.53s.) If we use MREPF algorithm, the sensed grid size used to calculate the path was set to be 20×20 and the outside grid size was set to be 10×10 giving a sampling rate of approximately 1.1s

In a completely static environment, the EPF planner may generate a complete path through a known environment in a single iteration. In this cases, the MREPF's performance is similar to EPF. Because of static environment, EPF calculate only for sensing data by using previously calculated node values. But in case of dynamic environment, consider the trade-off relation of EPF. When the robot met the unknown object such as obstacles, the EPF has to calculate the overall nodes in the dynamic programming to solve navigation problem. It takes a long time to solve, so the designer set the grid size large to operate in real time. In the MREPF, the specific large map that containing unknown object will be updated and it calculate the rough path in the large map. It doesn't takes a long time and the robot is able to navigate in static environment. And also the designer can set the grid size smaller than EPF to operate in real time. The memory size is also compared. In the EPF, the dynamic programming solves for the all grid that means the dynamic programming nodes have to contain all potential values and previous minimum node number. In the MREPF, the dynamic programming solves for the large map grid and current sensing region for next goal. It's number is small comparing to EPF and when a navigation region is large, the efficiency will be larger.

IV. Conclusion

For the mobile robot navigation, rapid decision is essential. The proposed method gives the rapid decision to robot using multi resolution technique based on EPF. The MREPF is well operate and works efficiently in dynamic environment. The large scale map interacts with small scale map as sequencer in Atlantis model. The dynamic programming is used to build up large scale map and a system of linearly independent equations is solved to generate two related fields, the scaler potential field and the vector current field. Tracing a path of maximum current flow through the branches of the network is equivalent to tracing a path of minimum resistance that maps to a minimum occupancy path. To do this in large scale map determines rough optimal path. To do this in sensing data map determined optimal path to next goal. The simulation studies show the efficiency of the proposed algorithm. The future works is extending this algorithm to SLAM and using vision sensor.

V. Further Work

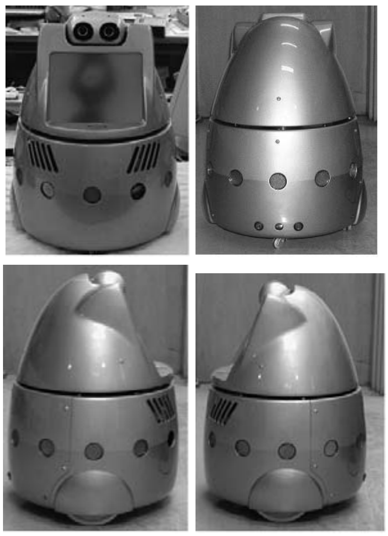

Fig. 8. Target Robot with 12 ultrasonic sensor: The experimental 2 wheeled mobile robot base.

Fig.8 is the experimental 2 wheeled mobile robot base. We will experiment the MREPF algorithm with this robot and report the results. The trade-off comparison must be added to prove the efficiency of our algorithm. The various size of grid must be tested in EPF and MREPF.

To experiment in real environment, the localization problem must be considered. The SLAM or Monte-Carlo localization will be tested for navigation in near future.

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