Real-time Path Planning For Senor-based Mobile Robot Based On Probabilistic Roadmap Method

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Abstract
This paper presents a new real-time path planning approach, which is based on the algorithm of probabilistic roadmap, for senor-based mobile robot in unknown environments. The novel idea is that the algorithm changes the on-line navigation problem into off-line one, which makes the work simple. Once the path planning problem becomes finding a way in already known environment, we can use traditional PRM to solve it. Thus, our idea is to guide the robot to make real-time global route planning each step, during the whole planning process, so that the knowledge of the environment is updated gradually. Therefore, the problems of path planning in unknown environments is turned into the problem of that in already known environments in each step. The purpose of the new method is to build a path that not only is relatively the shortest, but also avoids the local minima and other problems effectively. Some experimental results are presented in this paper to strengthen the new proposal.

Key words Probabilistic roadmap, path planning

I, Introduction

There are two main branches dealing with the path planning problem for mobile robot. The first one is about looking for a path in a previously known environment map, in which we can use some fast and effective methods such as the Rapidly Exploring Random Trees (RRT), the Probabilistic Roadmap (PRM)[1,2,3]and the Artificial Potential Field (APF), etc. The second type is for sensor mounted mobile robot to generate a path in an unknown environment, and in this case, methods like Hierarchical Generalized Voronoi Graph (HGVG), BUG and APF have already been used. The problem we are discussing in this work belongs to the latter, that is, a robot equipped with sensors is given a task to move from a set beginning point to a goal, in a completely unknown environment.

To direct the robot to generate an effective path, Lumelsky have done great job on BUG algorithm, which is simple but practical in this problem, so is HGVG, raised by Choset and Burdick, however, both of these two may generate redundant paths. The APF algorithm is also effective in real time avoiding obstacles and planning paths, but it has to face the local minima problem, which may cause the oscillation of the path. Because each approach has its own flaws, therefore new and faster methods are still needed in this case. In [4], Claudio raised a method about using improved PRM to resolve the on line navigation problem, which brought a new way to develop PRM in the path planning field. Although the paths that generated by Claudio's algorithm is not too effective when the environment gets complex, it could help the robot to succeed in many cases. The new method that presented in this paper is also based on PRM to solve this kind of problem, but the difference between it and the Claudio's is that our new proposal still uses the traditional PRM to generate a path in the already known maps, but not the Lazy-DRM or other improved PRM. And the most important discrimination is we use PRM more than once in the whole process, that is to say, the randomly distributed nodes that generated by PRM are not uniform during the task.

The rest of this paper is organized as follows. In section II theories relevant with the new approach are provided. Section III contains a detailed and complete description of our method. In section IV several simulations are provided with which the new approach is evaluated. In the final section we draw the conclusions and the future work are also presented.

II, Probabilistic path planning

In this section we briefly introduce the main theory of the Probabilistic Roadmap method. The framework of PRM planning algorithm consists of two phases: roadmap construction (learning) and query. In the learning phase, the algorithm constructs a probabilistic roadmap by generating random free configurations of the robot and connecting them using a simple, but very fast motion planer, also known as a *local planner*. And then the connected roadmap is stored as a graph whose nodes are the configurations and whose edges are the paths computed by the local planner. In the query phase, a path will be found from the start and goal configurations to two nodes of the roadmap. Then the planner searches the graph to find a sequence of edges connecting those nodes in the roadmap, and finally a feasible path for the robot is generated by concatenating the successive segments. If each segment between its two ending nodes is the shortest one among the segments connecting the same couple nodes, and if between any two nodes in the path, no more effective connection could be found, the path we got is the relatively shortest way from the start to the goal. The following figure gives a simulation result of probabilistic planning in which a feasible path is found quickly by PRM.

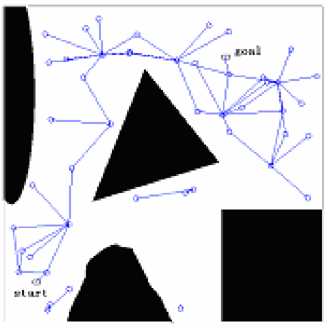

Figure 1 An example of planning result with the method of PRM. In the figure there is a path generated from start to the goal.

The new theory presented in this work is mainly based on the conventional PRM method, and uses it in the case of on-line path planning. In the next section, we will describe the new method in detailed.

III, The Proposed Method

A, The robot

The robot we are using in this paper is car-like mobile robot with sonar sensors all around. All the sensors are regarded as the nearly ideal sensors which can detect well and truly, so that it can *know everything* near it within the detection region. The robot's task is to go to a set target from a given beginning point in an unknown environment. In order to simplify the planning problem, we treat the mobile robot as a represented point in the rest of this paper. We also suppose the robot has self-localization equipment in order that it always knows its own position in the coordinate space of the environment during its motion. In fact self-localization may bring some errors on the positions, which affects the effectiveness of the approach. In this paper we do not consider the error brought by the self-localization, and it is supposed that the robot can get its real time position exactly.

B, The algorithm

Our new proposal is a real-time path planning approach which is based on the method of probabilistic roadmap, and it helps the robot to generate a new and accessible path in the unknown environments. To study it more easily, we call the new method as Real-time PRM. The novel idea of real-time PRM is its combining the problems of route planning both in previously known environment and unknown situation. In each step of the robot's moving, the sensors will collect the new information from the environment, and then an updated map is generated in which there are the circumstances already detected by the robot so far. According to this map, a most effective path from the current configuration to the target could be found with PRM method. Subsequently, the robot goes along the newly built way until it meets new situation, and if so, it means this loop ends and another one just begins, and the renewable map will be updated again. In the algorithm we call this map as built_map. The built_map is a bitmap which is described by a 2 dimension matrix in the database of the robot and it has the same size with the physical environment map. During the task, built_map is generated and updated gradually, which represents the robot's increasing knowledge about the environment. Each time after the renewal of the built_map, the algorithm replans a new path with PRM for the robot to move along. When the robot *sees* new obstacles at point A in the environment, the algorithm firstly calculates the coordinates of A with the knowledge of this path, and then computes the positions of the collision detected.

The real-time PRM can be divided into two steps that are described as follows:

1, The robot arrives at a new point in the environment map; update the built_map with the feedback knowledge of the sensors; go to step 2;

2, In the built_map, find the shortest path from the current point of the robot to the goal with the method of PRM; the robot moves along this path until each of the following things happens:

I, some new obstacles are detected by the sensors, go to step 1.

II, the robot reaches the target, stop.

To generate the shortest path from the current point of the robot to the target with PRM, we need to use the following process:

Generate a set number of randomly distributed points in the built map.

↓

Delete the points that are covered by the obstacles.

↓

Connect every two points within the sensor's detection region, and eliminate the segments that cross the obstacles.

↓

If several separated parted are generated, then build more nodes between these parts.

↓

From the figure that composed by the edges and the nodes, choose the shortest path from the start point to the goal.

Figure 2

The pseudo-code of the algorithm is given in table 1

Table 1

$M \leftarrow \phi$
$P_0 \leftarrow$ the start point
$P_i \leftarrow$ the current point
$P_g \leftarrow$ the goal
$i \leftarrow 1$
Loop
If $P_i = P_g$
  The robot arrives at the goal, and the path is generated.
  Return
Else
  Obst(i) $\leftarrow$ the obstacles information got by the robot at P_i
  N $\leftarrow$ M $\cup$ Obst(i)
  if M!=N
    M $\leftarrow$ N
    Path(i) $\leftarrow$ the shortest path built by PRM in M, from current point to Target
    $P_{i+1} \leftarrow$ the next point after the current in Path(i)
  else $P_{i+1} \leftarrow$ the next point after the current in Path(i-1)
End
The robot goes to P_{i+1}, i $\leftarrow i+1$

The number of the random nodes that the algorithm generated is directly relevant to the results, but it the number is too big, then the consuming time will increase dramatically. Therefore the number should be chosen carefully.

IV, Experimental results

In this section the results of some simulations are presented, which show the robustness of the new algorithm. To make our point clearly, we present a complete detailed process of the planning. In these simulations, the environment maps we use are all squares with the size of 50mX50m, and the sensor's maximal detection distance is set as 3m. The number of the probabilistic nodes that generated in each of the robot is set as 200 in experiments. The following experiments are completed on a PC with Pentium IV 2.4G CPU and the algorithm was executed in Matlab. The following figure is the environment map used in the simulation.

Figure 3 The environment map for the simulation. In the figure, the dark areas represent the obstacles.

Figure 5 shows 12 slips of the whole process, each of which is a built_map in the current step. In each slip, the random nodes are regenerated, and the shadow represents the obstacles that are detected by the sensors. More shadow means more information of the environment is got by the robot and the built_map has been updated. The path in each slip is different from each other because it is only built by PRM in that situation. The nodes in the paths that are represented by "o" means the real track passed by the robot in the previous steps, whereas the nodes still described by "*" are the nodes of the new generated route. The path in the last slip is the final path from the start to the goal, which can be seen clearly in figure 4.

Figure 4 The final path.

V, Conclusion and Future work

This paper presents a new motion planning method which develops the trditional PRM on the path planning problems in unknown environments. The main contribution of this work lies in it simplifies the on-line planning to many static computing processes. From the simulation results we can find that the path built by the real time PRM is effective and in built_map a part of the environmental information is stored, which also benifits to map-building work. However, to further evaluate the robutness of the new algorithm, more comparison of the distance and the computing time and other charaters with other methods are necessary, which is work we will do in the future. And the error of the sensors will be considered too in our future work.

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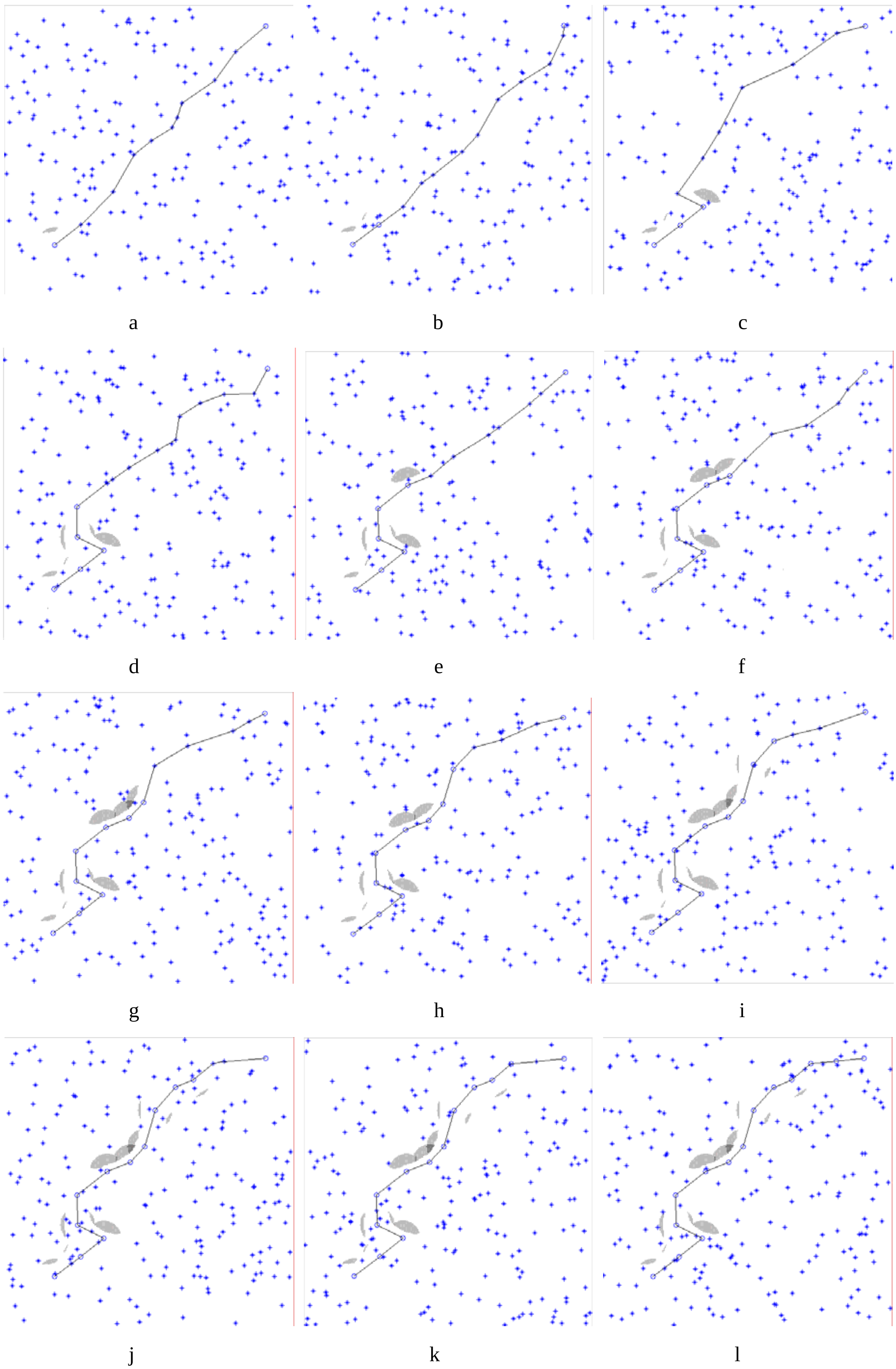

Figure 5