ACS-PRM: Adaptive Cross Sampling Based Probabilistic Roadmap for Multi-robot Motion Planning

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Abstract In this paper we present a novel approach to multi-robot motion planning by using a probabilistic roadmap (PRM) based on adaptive cross sampling (ACS). The proposed approach, we call ACS-PRM, consists of three steps, which are C-space sampling, roadmap building and motion planning. Firstly, a sufficient number of points should be generated in C-space on an occupancy grid map by using an adaptive cross sampling method. Secondly, a roadmap should be built while the potential targets and milestones are extracted by post-processing the result of sampling. Finally, the motion of robots should be planned by querying the constructed roadmap. In contrast to previous approaches, our ACS-PRM approach is designed to plan separate kinematic paths for multiple robots to minimize the problem of congestion and collision in an effective way so as to improve the planning efficiency. Our approach has been implemented and evaluated in simulation. The experimental results demonstrate the total planning time can be significantly reduced by our ACS-PRM approach compared with previous approaches.

1 Introduction

Motion planning is a fundamental problem in robotics. It could be explained as producing a continuous motion for an agent, that connects a start configuration and a goal configuration, and avoid collision with any static obstacles or other agents in an environment. Agent and obstacle geometry are generally described in a 2D or 3D workspace, and the motion could be represented as a path in configuration space. Motion planning algorithms are widely applied in many fields, such as bioinformatics, robotic surgery, industrial automation, planetary exploration, and intelligent transportation system.

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The multi-robot system (MRS) is proposed to deal with some problems that are difficult or impossible to be solved by a single robot, or to improve the system implementation efficiency in some missions completed by multi-robot rather than a single robot [1], [2]. The biggest challenge for the MRS is coordination. Without coordination, it will not only lower the system efficiency, but also lead to the failure of the entire system in extreme cases. In this paper, we consider the issue of coordinated motion planning for a homogeneous team of autonomous mobile robots in structured environments. Most of the proposed approaches for multi-robot motion planning usually have the problems of resource conflict such as congestion and collision [5], [9]. We arrange these cases to the waiting situation problem [10]. To handle this practical problem, this paper presents a novel approach for multi-robot motion planning by using a probabilistic roadmap planner (PRM) which is based on manner of adaptive cross sampling (ACS).

The rest of the paper is organized as follows: Section 2 describes an overview of some related works; Section 3 describes our ACS-PRM approach; Section 4 presents the experimental results obtained with our approach; and the paper is concluded in Section 5 at last.

2 Related Work

In our previous work [10], we considered the issue of using separate topological graphs to coordinated multi-robot motion planning for exploration mission. This work aims at solving the waiting situations in the process of the robot motion planning. In particular, if all the robots take the same topological graph derived from grid map, then they might follow the same exploration path partly or wholly, and this contributes to the problem of waiting situation. We proposed an approach based on sampling environment map iteratively to support the coordinated multi-robot exploration. This research is related to the approach proposed in this paper, even if the methodology is substantially different. Compared to our previous approach, we obtain a significantly reduced mapping time by this approach.

Our recent research focuses on the issue of multi-robot goods transportation [11]. The objective is to complete the transportation mission with high efficiency and low cost. We proposed a heuristic method based on the empirical model, which aims at planning the transportation task for each individual robot by estimating the production rate of goods based on multi-robot coordination, so as to improve the system performance. In the module of robot motion planning, we used the wavefront propagation algorithm to global path planning and the nearness diagram algorithm to goal seeking and local obstacle avoidance. Nevertheless, in the experiment, one important reason which influences the system performance is still the waiting situation. Furthermore, if the speed of the robot is too fast, then the goods would be damaged or lost in transit because of the collisions with obstacles or other robots. We limited the speed of the robot to handle this problem, whereas this strategy limited the efficiency of the whole transportation system as well. Therefore, in this paper we discuss the essence of the problem and propose a novel approach to address such problems.

3 ACS-PRM: Adaptive Cross Sampling Based Probabilistic Roadmap

Sampling-based approaches have been proposed to improve the computational efficiency for robot motion planning. The main idea is to avoid the explicit construction of the obstacle region in the C-space (C_{obs}). Unlike the incremental heuristic search such as A* or D* and the topological map methods such as Voronoi diagram or straight skeleton, the sampling-based approaches work well for complex environments and high-dimensional configuration spaces, and they are generally easier to implement. The probabilistic roadmap planner is one of the typical sampling-based approaches. The original PRM technique is introduced by Kavraki *et al.* [4], which has been shown to perform well in a variety of situations. On the basis of this method, different extensions have been proposed [8], [6]. The approach described in this paper is also an extension of PRM, which is aimed at performing multi-robot motion planning efficiently.

3.1 C-space Sampling

The ACS-PRM approach presented in this paper is a multi-query approach. The first step is C-space sampling, in which a sufficient number of points should be generated to represent the free space of the environment. The main idea of this step is to let a random point p retracts to a position $P(q)$ with the distance d to the obstacle C_{obs} along horizontal and vertical directions (i.e., cross direction).

For autonomous nonholonomic mobile robots, in two dimensions, there are three representational degrees of freedom (DOFs) which are one rotational DOF and two translational DOFs (along or across), but only two controllable DOFs which only move by a forward motion and a steering angle, the configuration space C is the special Euclidean group $SE(2) = \mathbb{R}^2 \times SO(2)$ where $SO(2)$ is the special orthogonal group of 2D rotations. To avoid the collision caused by the point retracts too close to the obstacle, we set the distance d as the sum of the positive number w and the radius r of the minimum circle to cover the robot with centering at the rotation center of the robot:

$$d = r + w, \ (w > 0) \tag{1}$$

The set of w is to deal with the negative influence of sensor error and it should be adjusted in practical applications.

C_{obs} represents the set of the obstacle, $\forall q \in C_{obs}$ define a direction r_q, then determine a symmetry point $S(q)$ which is an intersection of the open-ray with end q direction r_q and another C_{obs}:

$$S(q) = \{q + t\overrightarrow{r_q} | t > 0\} \cap C_{obs} \tag{2}$$

where, if $\{q + t\overrightarrow{r_q} | t > 0\} \cap C_{obs} = \{q\}$, then define $S(q) = \infty$. Let $dist(x,y)$ represent the distance between point x and point y, then the retraction function can be described as:

$$P(q) = \begin{cases} q + d\overrightarrow{r_q} & \text{if } dist(q,S(q)) \geq 2d \\ \frac{q+S(q)}{2} & \text{otherwise} \end{cases} \tag{3}$$

where $P(q)$ is the position for the point p to retract. In this way, the random points are adapted around to the obstacle (see Figure 1(b)), then:

$$\text{ACS-PRM} = \{P(q)\} | q \in C_{obs}\} \tag{4}$$

The implementation of this step is summarized in Algorithm 1, where the time complexity is $O(n)$ and the space complexity is $O(1)$. This step corresponds the learning phase of classic implementation of PRM.

Algorithm 1 Adaptive cross sampling

Require: N, the sufficient number of points to generate.
Ensure: N points in C_{free} by adaptive cross sampling.
repeat
  Generate a uniformly random point p in C-space.
  if p is free **then**
    for horizontal and vertical directions **do**
      Find $q \in C_{obs}$ the nearest distance from p.
      if $dist(p,q) \geq d$ **then**
        p retracts to $q + d\overrightarrow{r_q}$.
      else
        Find $\{S(q)\} = \overrightarrow{qp} \cap C_{obs}$.
        p retracts to $\frac{q+S(q)}{2}$.
      end if
    end for
  end if
until N points have been generated.

3.2 Roadmap Building

The second step is roadmap building, in which the potential targets and milestones should be extracted and connected to the roadmap. In the previous step C-space

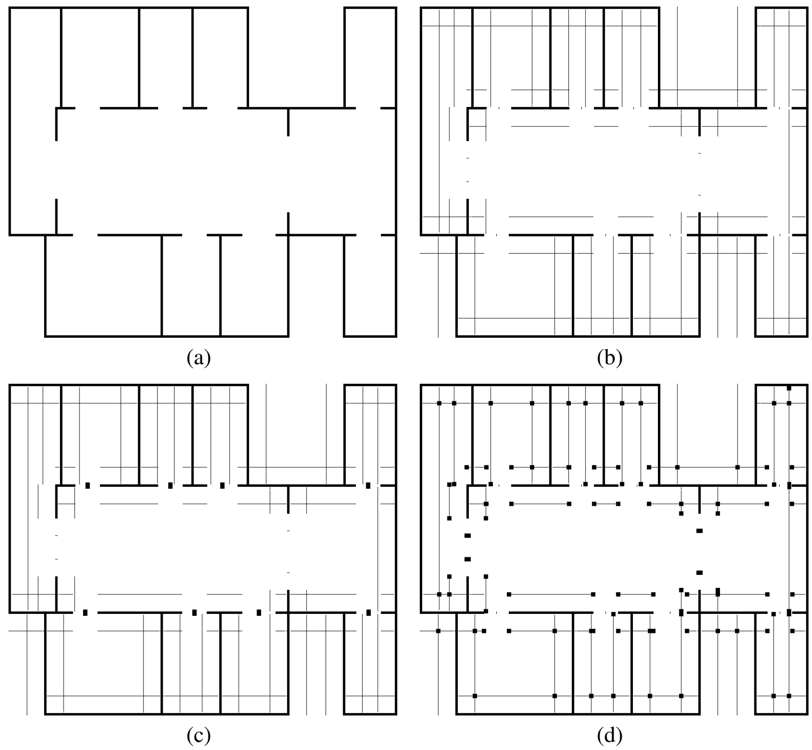


Fig. 1 Generation of the roadmap based on ACS-PRM. (a) The original gridmap, (b) adaptive cross sampling in C-space, (c) the extracted potential targets (doorways), and (d) the extracted milestones.

sampling, if there are sufficient points generated, then the points will gather into segments. The main idea of this step is post-processing the graph resulted from the previous step while identifying three types of point as follows:

- In the previous step, if $dist(p,q) < d$, then p will retract to $\frac{q+S(q)}{2}$ and be labeled as the medial axis. Therefore, we find those medial axis segments with length l a small fixed value (in our implementation, we took the thickness of obstacle), and the midpoints of segments are marked as *potential target* for task allocation. Figure 1(c) shows the extracted potential targets which are precisely doorways of the structured environment.
- For those segments without containing the potential target, we extract both of the endpoints and mark them as *milestone* (see Figure 1(d)).
- The points of intersection between two segments are also extracted and marked as *milestone* (see Figure 1(d)). These milestones have not been used in our experiments, but they will be required for the exploration problem.

This step also corresponds the learning phase of classic implementation of PRM. Figure 1 illustrates the process of generating a roadmap for an example occupancy grid map by using our approach with 200,000 random samples.

3.3 Motion Planning

The third step is motion planning, in which each individual robot's kinematic path should be planned by querying the constructed roadmap. The main idea of this step includes the following three points:

- The potential targets $\{t_i\}$ are considered as the goal nodes for path planning and the objects for task allocation as well. Then, the individual $\{r_i\}$ robots are assigned to different potential target:

$$\{r_i\} \mapsto \{t_i\} \tag{5}$$

- To maximize the difference between the paths, we assign the potential target which is the closest from the robot but further from the previously assigned target to the current individual robot:

$$t = further(closest(\{t_i\}, r), t_{i-1}) \tag{6}$$

- Similar to the classic PRM, we use the fast local planning method (i.e., the straight line planner) for the global path planning, except that we choose the path with the minimum number of milestones for the robots invariably.

This step corresponds the query phase of classic implementation of PRM.

4 Experiments

To evaluate our ACS-PRM approach, we conducted a series of simulation experiments with the 2D multi-robot simulator Stage [3]. The experiment is to transport a certain amount of goods from one origination to divers destinations by a fleet of mobile robots. The simulated robot is the Pioneer 2-DX robot equipped with a laser range finder providing 361 samples with 180 degrees field of view and a maximum range of 8 meters. Each robot can localize itself based on an abstract localization device which models the implementation of GPS or SLAM. To transport goods, the robots are equipped with a gripper that enable them to sense, pick up and put down the goods, and the carrying capacity is limited to one unit per robot.

We used a different number of robots to conduct several experiments in various environments. Two maps (Figure 2) were used in our simulation which are both structured environments. For each map, the green area signifies the original position of goods, and the yellow areas represent the destinations which are always placed in

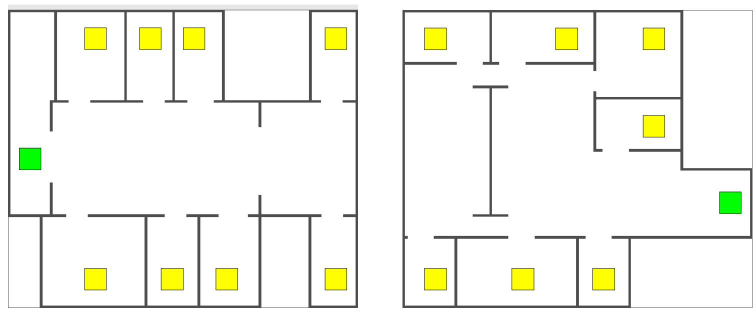
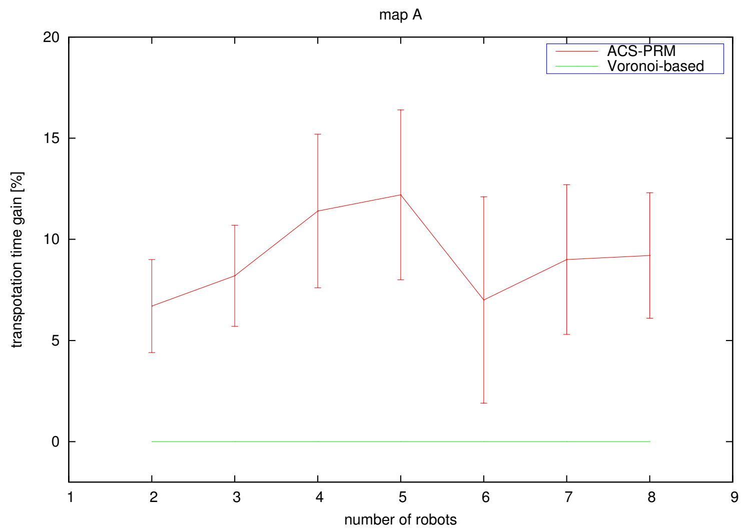


Fig. 2 Two environment maps used in our simulation.

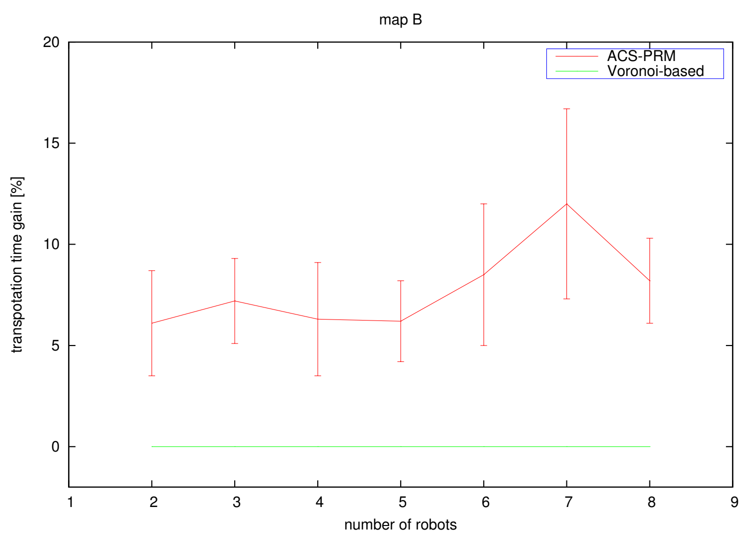
the rooms. The transportation team size is varied from 2 to 8 robots. On each team size, 10 experimental runs are performed for a transportation mission of 50 goods. The mission objective is to transport the goods to every room equally. The ratio between real-world time and simulation time is about 1:1. We also compared our approach to the commonly used Voronoi-based approach [7] in which a topological map is built on top of the grid map by using the Voronoi diagram, and the *critical points* are extracted like milestones for mobile robot motion planning. All experiments reported in this paper were carried out on a system with an Intel Core 2 Duo E8400 3.00GHz processor, an Intel Q43 Express chipset and two DDR2 800MHz 1024MB dual channel memory.

In the experiments, we assumed that there exists a central server which is able to communicate with all mobile robots and assign the transportation tasks to each individual robot. The results of our experiments are given in Figure 3. We measured the transportation time gained by our approach and compared to the Voronoi-based approach. In each plot, the abscissa denotes the team size of the mobile robots, the ordinate denotes the percentage of the transportation time in the total transportation time, and the error bar indicates the confidence interval of each corresponding gain of robot team size with the 0.95 confidence level. Figure 3 shows that, a transportation time saving of 6.7% to 12.2% in map A and 6.1% to 12.0% in map B is obtainable under our ACS-PRM approach compared to the Voronoi-based approach. These results proved that our technique could significantly improve the system planning efficiency.

Moreover, we mentioned earlier that our ACS-PRM approach is more effective than our previous approach because the ACS-PRM spends much less time for the learning phase. The experiments show that, with the new approach, the mapping times are respectively 0.321 seconds and 0.329 seconds for map A and map B with 200,000 random samples, which are averages of the 10 runs. We also counted the average number of occurrences of waypoint mutex in each map as shown in Table 1. This table shows that the problem of waiting situation is significantly reduced by using our ACS-PRM approach, because our approach is able to plan separate paths



(a) map A



(b) map B

Fig. 3 Transportation time gained by using our ACS-PRM approach compared with the Voronoi-based approach.

for robots, especially in the corridor. Unlike the Voronoi-based approach, there is only one path for all robots.

Table 1 Statistics of the number of occurrences of the waypoint mutex

(a) map A

#robots	2	3	4	5	6	7	8
ACS-PRM	1.6	3.1	6.4	7.5	10.0	11.1	16.2
Voronoi-based	15.3	18.7	26.0	26.8	19.9	23.7	27.2

(b) map B

#robots	2	3	4	5	6	7	8
ACS-PRM	3.8	4.3	7.1	14.9	12.8	10.3	16.7
Voronoi-based	17.1	19.2	19.0	26.5	27.4	27.0	29.9

5 Conclusion

In this paper, we presented a novel approach for coordinated motion planning of multiple robots by using the probabilistic roadmap planner based on a manner of adaptive cross sampling, which we called ACS-PRM. The basic thought of the proposed approach is to build separate kinematic paths for multiple robots to minimize the problem of waiting situation such as collision and congestion caused by waypoint mutex in an effective way, thus to improve the efficiency of automated planning and scheduling. In consideration of the context of the issue of multi-robot goods transportation, the experiments were conducted to transport a certain amount of goods by a fleet of mobile robots in structured environments. The experimental results demonstrate that, by using our ACS-PRM approach, the total time needed to complete the transportation mission has been significantly reduced compared to the Voronoi-based approach.

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