A NEW HYBRID SAMPLING STRATEGY FOR PRM PLANNERS

To Address Narrow Passages Problem

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Abstract: The probabilistic path planner (PPP) is a general planning scheme that yields fast robot path planners for a wide variety of problems, involving high degree of freedom articulated robots, non holonomic robots, and multiple robots. This paper presents a new probabilistic approach for finding paths through narrow passages. Our probabilistic planner follows the general framework of probabilistic roadmap (PRM), but to increase sample density in difficult areas like narrow passages, we define two sampling constraints in order to get much more points than a classic PRM gets in such areas. We simulate our planner in 2D environments and the simulations results shows good performance for our planner.

1 INTRODUCTION

Robot path planning, which asks for the computation of collision free paths in environments containing obstacles, has received a great deal of attention in the last decades The basic problem is about computing a collision free-path that brings the robot from his current position to some desired goal position. The space where the robot and the obstacles are physically present is called the workspace W, using the formalism introduces by (Lozano, 1983) the planning is mostly performed in another space, the configuration space C. Each placements of the robot in W is mapped to a point in C. The portion of C corresponding to collision-free placements of the robot is referred to as the free-configuration space CS_{free}. At the GREAH laboratory, a dynamic model of car like robot was done (Guerin 2005) and our work is to design an efficient path planner for this mobile robot.

During the past decades probabilistic roadmap (PRM) (Kavraki, 1994) (Horsch, 1994) (Svestka, Overmars, 1995) (Svestka, Vleugels, 1995) has emerged as a powerful framework for path planning of robots with many degrees of freedom. The main idea of (PRM) is to sample at random a robot's configuration space and connect the sampled points to construct a roadmaps graph, which captures the connectivity of the free space. Despite the success of (PRM) planners, path planning with many degrees of freedom is difficult and even uncertain.

The first difficulty is laid in many cases to the higher computational cost paid by (PRM) to construct the roadmap graph, indeed (PRM) spends a lot of time in checking collision-free connections between all the sample points.

The second difficulty remains a classic problem of (PRM) planners. Sampling points in difficult areas like narrow passages pose significant problem, because narrow passages have small volumes and the probability of sampling from small sets is low.

In this paper, we propose a new probabilistic approach that reduces the computational cost of classic (PRM) planners and increases sample density of points in narrow passages.

The key idea to reduce the computational cost of (PRM) planner is to construct a single road instead of roadmaps, our planner connects the starting configuration to the goal configuration by generating random configuration from CS_{free}, and constructs one single local path that connect this current configuration to the immediate configuration generated before by our planner. Thus, collision-free connection is made only between two configurations, instead of the all existent configurations. We exploit the notion of "visibility set" (Barraquand, 1997) (Hsu, 1999) and also used

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in (Nissoux, 1999), to define a termination condition for our planner. Two points of the configurations space are considered visible to each other if they can be connected by a collision-free straight line path.
To improve the sample density in narrow passages we define a local planner that given two configurations, sample the path connecting them, and extract a new collision-free straight line path. We add to these local planner two constraints. The predefined distance that our local planner uses to sample near the current configuration, and the angular constraint that guarantee always for our mobile robot moving towards the goal configuration. Section (2) reviews related work on sampling configurations in narrow passages, section (3) gives an overview of our planner, section (4) analyses our algorithm section (5) presents some resulting paths from simulations and comments them, section (6) make a general conclusions about our planner and presents the future extension of this work.

2 RELATED WORK

The difficulty posed by narrow passages and its importance, were noted in early worm in PRM planners. One possibility is to sample more densely near the obstacles boundaries (Boor, 1999) (Collins, 2003). The Gaussian sampler uses this idea (Boor, 1999). However, in some cases many points near obstacles boundaries lie far from narrow passages and do not improves the connectivity of roadmaps. Other approaches to narrow passages sampling includes dilating free spaces (Hsu, 1998), and retracting to the medial axis of free spaces (Wilmarth, 1999). Both approaches require a high geometric computation time in high dimensional configuration spaces

3 OVERWIEW OF THE PLANNER

In this paper we follow the general framework of (PRM), but our planer computes one single road which connects the starting and the goal configuration with always sampling random configuration from CS_{free}. The local planner then, connects only the current randomly selected configuration with the previous configuration added before. We name our planner the probabilistic single road planner (PSRP). The idea is to try to get a simple algorithm that reduces the computational cost of (PRM). Intuitively by checking collision free connection only between two milestones our (PSRP) will save a lot of computation time rather than spending at checking collision free connection between all milestones generated by (PRM). The design of our algorithm is based on tree components defined below.

3.1 Visibility Path

Consider a robot $\Re$ moving in a workspace $\Im$ let CS be the configuration space of the robot. Let CS_{free} be the collision free configuration space in $\Im$. Let L be any local planner that computes a path $L(q,q^{'})$ (e.g. straight line segment) between two given configurations q and $q^{'}$. We define the visibility domain of a configuration q for L by:

$$Visi_{L}(q) = \{q^{'} \in F, L(q,q^{'}) \in F\},(1)$$

We use this relation to define a new domain of visibility. Given q_{goal}, two configurations q and $q^{'}$ the path computed by the local planner, is sampled at n points x_i and the new visibility domain is defined as following:

$$Visi_{L}(x_i) = \{q_{goal} \in F, L(x_i,q_{goal}) \in F\},(2)$$

Where $F = CS_{free}$

3.2 Distance Sampling

Our local planner uses a threshold distance to connect only milestones within this predefined distance.

3.3 Angular Sampling

The second constraints is about an angular sampling to guide the search of a solution path toward the goal configuration see (Figure 1) In figure (1) we consider that our algorithm samples milestone1 and is able to sample two possible milestones (milestone 2 and $2^{'}$). For each possible milestone our planer put a predefined angular constraint $\theta i_{constraint}$ on the difference of the size of the angle between milestone 1 and one of the possible current milestones 2, $2^{'}$

and, the angle between milestone 1 and the goal milestones.

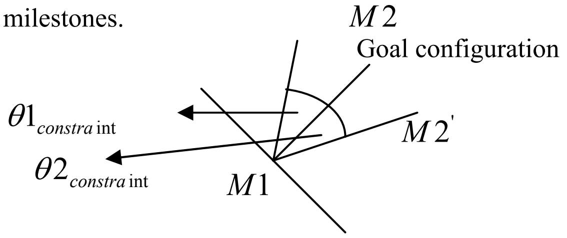

Figure 1: Angular sampling.

The algorithm of angular sampling is given as follows:

Algorithm1: Randomized angular sampling

1. Repeat
2. Pick M1, M2 from F /*M1, M2: milestones
3. $\theta_1 \leftarrow$ Angle ($\overrightarrow{M_1 M_{goal}}$, Ox).
4. $\theta_2 \leftarrow$ Angle ($\overrightarrow{M_1 M_2}$, Ox)

4 **if** ($\theta_1 - \theta_2 \leq \theta_{constraint}$) **then** add M1, M2 to G

5. **Else** goes to 1.

4 ANLYSES OF (PSRP)

Our algorithm is designed to reduce computational cost resulting from (PRM) and this, by using the two sampling constraints we defined above, the notion of visibility (3.1) and. local geometry tests. We define the function f as follows:

$$f = 1 \quad \text{If} \quad L(x_i, q_{goal}) \in CS_{free} \tag{3}$$

The key idea of this strategy is about the local path computed between two configurations q and q' (i.e. two milestones) randomly picked. Clearly our algorithm samples this path at points x_i, and a collision free test is made on each point, a path is computed between q and the last x_i returning a positive response for the collision free test.

We also use the idea of hybrid sampling, by combining our local planner, with the two constraints presented in (3.2) and (3.3) to increase sampling in narrow passages. A simplify version of our algorithm is given:

1. q_{start}

2 $f \leftarrow 0$

3. M1 $\leftarrow q_{start}$

4 **while** ($f = 0$)

5. Select a random free configuration M2

6. Compute θ_1, θ_2, d /* d: the distance between M1and M2

7. If ($(\theta_1 - \theta_2 \leq \theta_{constraint})$^$(d \leq D_{\max})$) then

8 sample line segment M1M2 at x_i points

9. Check collision at each x_i for M1M2 and $x_i\ q_{goal}$

10 if ($f = 1$) then

11. Create edge ($M_1 x_i$) $\cup$ edge ($x_i q_{goal}$)

12 **else** create edge ($M_1 x_i$)

13 add x_i to G $M_1 \leftarrow x_i$

Assume that (PSRP) sample a milestone near obstacle, indeed our local planner compute local paths between one milestone and the last x_i point returning a negative response for the collision free test, thus we have a big probability to get one milestone near an obstacle boundary. By choosing a small predefined distance value, for example the width of the narrow passages, and the angular constraint to be less or equal to $pi/2$, we increase the sampling points at the narrow passages figure(2).

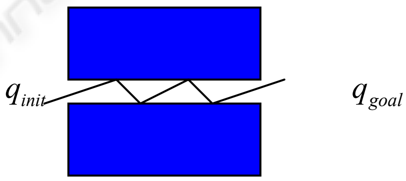

Figure 2: Computed path in narrow passages.

5 SIMULATIONS

We simulate our algorithm on Matlab/simulink software. To examine our planner performance we simulate it on several difficult environments with variation for each, the predefined distance and the angular opening constraints. We present some interesting resulting paths in the figures below:

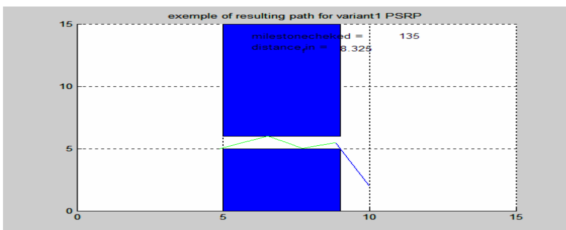

Figure 3: Computed path1 by the first variant of PSRP.

Fig.3: This environment contains two obstacles, separated by a small narrow passage area. We set the predefined distance constraint manually to be in [0, 8], the angular constraint was taken in $[0, \pi/2]$. The path computed in green colour presents the first variant algorithm contribution, the second path in blue colour shows the contribution of the visibility path component.

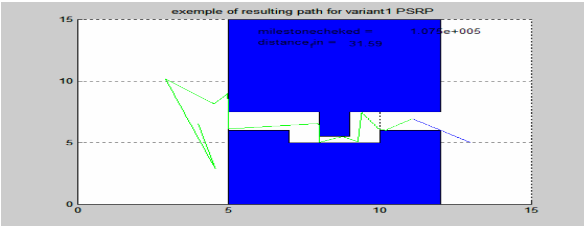

Figure 4: computed path2 by the first variant of PSRP.

Fig.4: The environment in Fig.9 presents many narrow passages. Our PSRP check a large number of milestones thus, increase T_{mil} , but sample only well-placed milestones

6 CONCLUSIONS AND FUTURE WORK

We have presented a new probabilistic approach to address the narrow passages problem. The simulating results show that (PSRP) gives an efficient response for this problem. The main issues that we are interested in exploring further in the future, is about the predefined distance and the angular constraints that are chosen manually, a promising approach is to adjust these two constraints through on- line learning by taking into accounts the obstacles positions.

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