Partition Sampling Strategy for Robot Motion Planning in Narrow Passage Under Uncertainty

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Abstract. To address the perception and motion uncertainty issues for motion planning in narrow passage environments, a Partitioned Sampling Strategy based on Partially Observable Markov Decision Processes (POMDP) is put forward. Combining the partition sampling strategy with the POMDP algorithm improves the success rate of robot motion planning under narrow channel. Firstly, the division sampling strategy is adopted to divide the robot workspace into open area and narrow area, and connecting fewer sampling points to generate the initial trajectory of the robot; After the initial trajectory is generated, we further consider the uncertainty factors to make the path performance better. The POMDP model is used to solve the uncertainty problem; the local optimal solution is obtained by solving the POMDP problem, and the local optimal solution is iterated until the global optimal trajectory is obtained. The belief dynamics uses Extended Kalman Filter updating, and the belief space variables of iterative LQG are used for value iteration. The experimental results show that the appeal scheme can solve the motion planning problem of the robot in the narrow channel and the uncertain condition.

Keywords: Motion Planning · POMDP · Uncertainty

1 Introduction

In recent years, with the rapid development of positioning and navigation technology, it is possible for mobile robots to navigate autonomously in unknown environment. However, even the most advanced Simultaneous localization and Mapping (SLAM) technology can bring uncertainty to the location of obstacles in the map due to the noise in the sensor. Although traditional path planning algorithms tend to ignore the existence of uncertainty factors because of the pursuit of computing speed, uncertainty factors must be considered in the process of mobile robot path planning [1].

Designing decision strategies for robotic systems under uncertainty is a considerable challenge [2]. Uncertainty arises from three sources. One is motion uncertainty. The uncertainty of the robot's motion process, usually due to wheel slip, or imperfect motion models. The second is sensor uncertainty, that is, the uncertainty in sensor readings.

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The third is map uncertainty, i.e., environmental features that cannot be fully observed [3]. The Partially Observable Markov Model (POMDP) is another form of environmental model where the current state is not completely known [4], extending the Markov Decision Process (MDP), where the agent can not get the state of the system directly, but only rely on the observer to get the possible state of the system indirectly, which is called belief [5]. Our goal is to find a strategy that selects the best action for each belief state to accomplish a task at minimal cost. This optimization problem is specified as a partially observable Markov decision process [6]. POMDP has become a widely used mathematical framework for dealing with uncertainty [7]. Point-based value iteration algorithm is a powerful tool to solve POMDP problem. It can be used not only in the situation of incomplete information, but also in complex high-dimensional systems [8].

In order to deal with nonlinear stochastic systems with control constraints, an iterative linear quadratic Gauss Scheme (iLQG) is put forward [9]. Pick out the sampling points [10] is also crucial when the RRT planner is looking for the initial trajectory. This paper proposes a partitioned sampling method based on importance sampling thought [11] to solve the path planning problem under narrow passage.

2 Definitions

2.1 Belief Definition

The room of all the probably states of the robot is represented by $X \in R^n$, the room of all the probably control information of the robot is represented by $U \in R^m$, and the room of all the probably measurement information of the robot is represented by $Z \in R^k$, The input of POMDP adopts stochastic dynamic model and observation model [12]:

$$x_{t+1} \sim p[x_t, u_t], z_t \sim p[z_t, x_t] \quad (1)$$

where $x_t \in X$, $u_t \in U$, $z_t \in Z$ are the robot's state, the received control information and the measured information at *t-time* separately.

The belief $b[x_t]$ of the robot is defined as:

$$b[x_t] = p\left[x_t | u_0, \ldots, u_{t-1}, z_1, \ldots, z_t\right] \quad (2)$$

Beliefs is molded by a Gaussian distribution function, and using an EKF to model the dynamics of dynamics. In particular, a stochastic kinematic model and a measurement model are defined in this paper:

$$x_{t+1} = f[x_t, u_t, m_t], m_t \sim N[0, I] \quad (3)$$

$$z_t = h[x_t, n_t], n_t \sim N[0, I] \quad (4)$$

Among them, m_t represents the movement noise, n_t represents the observation noise, and I is the identity matrix.

The belief is defined as follows:

$$b_t = (x_t, \sum\nolimits_t) \quad (5)$$

where x_t is the mean and $\sum_t$ is the variance. Initial belief $b_0 = (x_0, \sum_0)$ is given.

2.2 Narrow Passage Definition

In this paper, a known experimental environment is established, there are regular obstacles in the experimental environment. The narrow area is defined:

$$P = d/D \tag{6}$$

In this case, d indicates the diameter of the robot and D is the width of passage.

When the value of P is less than a fixed value, this region is considered to be a narrow channel.

3 Approach

The method presented in this article is described below. First, the map environment is divided into two spaces, then the initial path is obtained by partition sampling strategy, and the initial path is iterated until the optimal solution of the value function is found.

3.1 The Partitioned Gaussian Sampling Strategy

Path planning under narrow passage is a key issue, this paper put forword a partitioned gaussian sampling strategy, which dividing the environmental space into narrow and open areas. The open region is sampled uniformly and the narrow region is Gaussian sampling. The motion paths generated by partition Gaussian sampling are shown in Fig. 1.

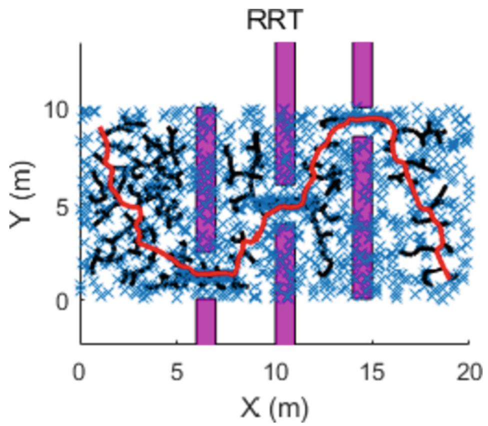

Fig. 1. The motion paths produced by partitioned Gaussian sampling.

After obtaining the initial path through the partitioned Gaussian sampling RRT planner, the path is used as input to solve the solution of the POMDP problem in order to obtain the final path.

3.2 Value Iteration

The value iteration is an effective scheme for solving POMDP problems. It address a series of value functions to ensure that the current task converges to the local optimal solution. The local optimal linear control strategy is obtained by performing value iteration on the belief space of iLQG.

The expected function, expressed by the following expression, indicates the minimum cost function:

$$c_t[b_t, u_t] = u_t^T R_t u_t + tr[\sum_t Q_t \sum_t] + f[\sigma[b_t]] \tag{7}$$

where $u_t^T R_t u_t$ penalty control action, $tr[\sum_t Q_t \sum_t]$ punishes uncertainty, and $f[\sigma[bt]]$ represents an obstacle cost term.

The value function is an approximately valid quadratic function surround the nominal path, expressed by the following expression:

$$v_t[b] = 1/2(b - \bar{b})^T S_t (b - \bar{b}) + (b - \bar{b})^T s_t + s_t' \tag{8}$$

where

$$s_t = \frac{\partial^2_{c_t}}{\partial b \partial b}\left[\bar{b}_t\right], s_t = \frac{\partial^2 t}{\partial b}\left[\bar{b}_t\right], s_t^{'} = c_t\left[\bar{b}_t\right]$$

4 Results

The point-like robot moves in a two-dimensional area with obstacles. The robot acquires measurement information through the four sensors it carries. In order to verify the effectiveness of the partition Gaussian sampling strategy, narrow lanes of different widths were created so that the robot could safely reach the target from the starting point with taking uncertainty into account. The experimental results are shown in Fig. 2.

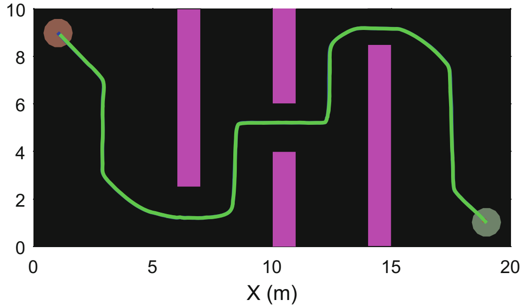

Fig. 2. Final trajectory.

4.1 The Influence of the Number of Sampling Points on Our Method

In order to further verify the effectiveness of partitioned Gaussian sampling, different numbers of sampling points are set in simulation experiments. With 250 sampling points as the interval, set the sampling points to 750, 1000, 1250, 1500, 1750, 2000, 2250, and 2500 respectively. The success rate of the algorithm at different sampling points will be calculated.

In the Fig. 3, The gray, yellow and blue lines indicate the success ratio of the robot in passing through a narrow passageway with obstacles using uniform sampling, partition uniform sampling and partition Gaussian sampling, respectively. Obviously, when the sampling points are set in the range of 750–2500, the partition Gaussian sampling method is used to make the robot pass through the narrow passage.

The success rate has been greatly improved. When the number of sampling points is 1500, the maximum increase can reach 60%. However, partition Gaussian sampling leads to higher algorithm complexity and longer sampling time.

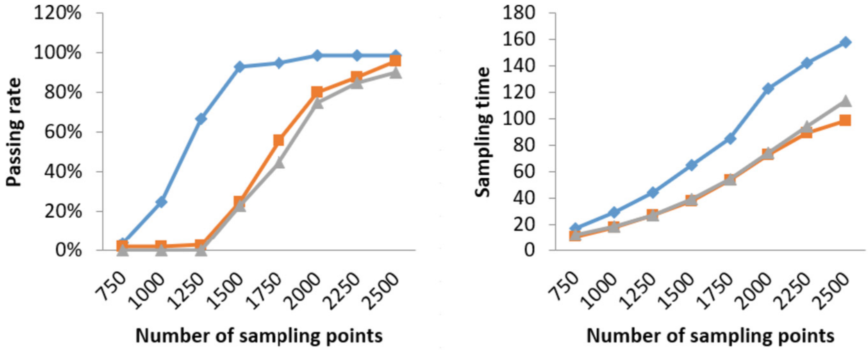

Fig. 3. The passing rate and sampling time of the robot. (Color figure online)

4.2 Path Cost and Security Analysis

After the initial path of the robot is obtained by partition Gaussian sampling, although the path is collision-free, it is likely to be unsmooth and very close to an obstacle, and a great deal of uncertainty accumulates in the process of execution. Taking this initial trajectory as input, calculating local optimal solution and corresponding control strategy can make the robot reach the target safely and cheaply, even if there is uncertainty in the environment. In order to analyze the advantages of iterative local optimal solutions, give the following two graphs (Fig. 4):

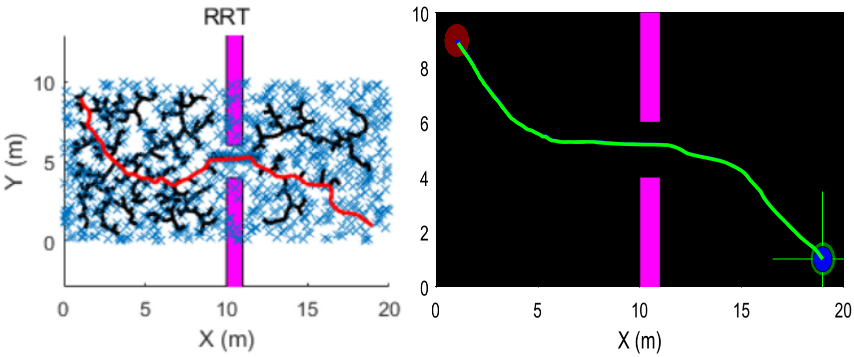

Fig. 4. The initial path and the optimized path

Point robots run in a two-dimensional plane with obstacles. The motion cost of the robot is 37 for the initial path and 20.9 for the optimal path. It can be seen that the value iteration method improves the safety of the robot and reduce path costs through narrow passage.

5 Conclusion

In order to solve the path planning problem in narrow passage, this paper proposes a partition Gaussian sampling strategy based on the idea of importance sampling. At the same time, we also consider the uncertainty problem in order to fit the actual situation better. The optimal trajectory of the robot is obtained in the process of value iteration based on POMDP, which improves the robustness of the path planning algorithm, it makes it easier for the robot to pass through the narrow channel under uncertain conditions.

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