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An universal GMMs-based sample strategy and collision checker for robot motion planning

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Abstract. The sampling-based motion planning methods acquire obstacle information by performing collision detection for a large number of samples, which can effectively solve autonomous obstacle avoidance problem in the high-dimensional configuration space. In order to improve the efficiency of planning, this paper proposes a new adaptive sampling strategy and collision checker based on Gaussian Mixture Models(GMMs): For the "narrow corridor" problem, the sample set obtained by Gaussian sampling strategy of adjustable standard deviation is used to train the GMMs. The models fitting the target area in the manipulator configuration space can guide the adaptive sampling; using the GMMs fitting the obstacle region to predict the collision probability of the samples rapidly, and using Greedy K-means initializes the EM algorithm to improve the fitting accuracy of the model. Finally, the sampling strategy and collision detection method are combined with various sampling-based motion planning algorithms, and multiple simulation experiments are carried out to verify the results. The results show that the proposed method has significantly improved planning efficiency compared with the traditional method.

1. Introduction

To improve the intelligence of manipulators, motion planning problem has been one of the focus research in recent years. The sampling-based motion planning[1], such as RRT, is an important means to solve the manipulator motion planning problem. The method by performing collision detection for a large number of samples to obtain obstacle information, can effectively explore the connectivity of high-dimensional configuration space. While RRT needs to frequently call the collision detection module during the whole motion planning process and collision detection uses about 90% of the entire planning time[2]. The origin sampling algorithm is a blind uniform random search for the entire space, which limits the convergence speed.

In this paper, our main contributions include: Propose an adaptive sampling strategy based on GMMs, combined with Gaussian sampling method with adjustable variance, which can effectively solve the problem of "narrow corridor"; Analyze the influence of different initialization parameters on the fitting accuracy of GMMs, a greedy K-means clustering algorithm based on the minimum square error convergence is proposed to initialize the EM algorithm; a fast collision probability prediction method based on GMMs is proposed; the method is applied to a variety of sample-based motion planning algorithms. Combined with multiple simulation experiments, the improvement of planning efficiency is verified.

The organizational structure of this paper is as follows: Section 2 introduces related work; Section 3 introduces the adaptive sample strategy; Section 4 introduces the GMMs-Based collision detection;



Section 5 shows experimental results; Section 6 makes a conclusion.

2. Related work

In order to improve the planning efficiency of RRT, scholars all over the world have started research. Several sampling method have been studied to reduce the number of collision checks[3]. In 2003, Hsu D et al. proposed a hybrid sampling strategy in the PRM framework[4]. In 2011, S Dalibard and JP Laumond et al. proposed a slow-diffusion algorithm[5]. In 2007, Burns B et al. proposed a utility guidance method [6]. In 2015, O Arslan et al proposed a planning strategy for learning the feasibility and heuristic values of samples in the previous planning process [7]. The above methods are mainly used to solve the low performance of uniform random sampling planning. There are also many collision detection algorithms for accelerating computation have been developed[8-9].

In this paper, we introduce a quickly collision checker and an adaptive sample strategy reducing the number of collision checks based on the learned GMMs.

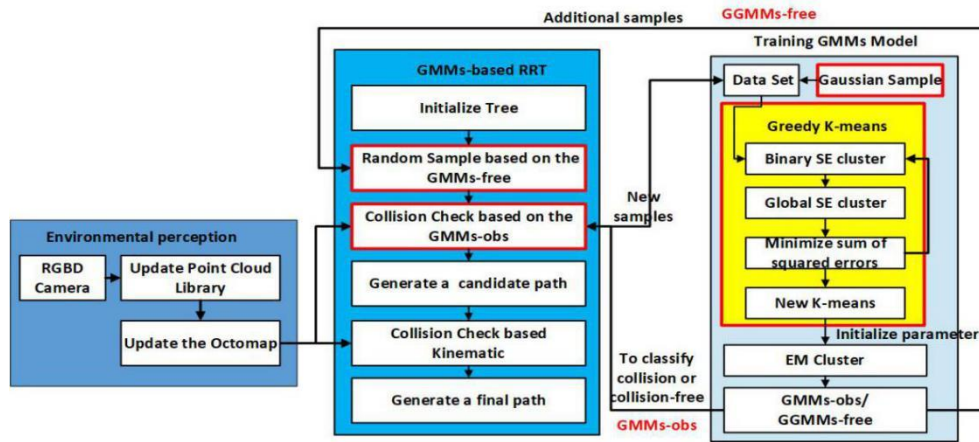


Figure 1. The overall algorithm framework about the improved GMMs-based motion planning. (Our main contributions are highlighted in red)

3. Adaptive Sample Strategy

GMMs use Gaussian probability density functions to accurately quantify things. GMMs linearly combine multiple Gaussian distribution functions with weights to fit arbitrary distributions, and thus achieve clustering of data sets. The GMMs fitting the distribution of the target area can narrow the search space by biasing random sampling and thereby reduce the number of collision checks. Figure 1 presents the overall algorithm framework about the improved GMMs-based sample motion planning. Table 1 shows the pseudo code of the GMMs-based RRT algorithm.

Table 1. GMMs-based RRT algorithm.

1. Require: V_{-free} by Gaussian Sample	8. Require: V_{-obs} samples
2. $GMMs_{-free} \leftarrow GMM.Train(V_{-free});$	9. $GMMs_{-obs} \leftarrow GMM.Train(V_{-obs});$
3. GMM Sample (q_{rand})	10. Compute: $P(q_{new})$
4. do	11. if $P(q_{new}) > \beta_{obs}$
5. NEAREST_NEIGHBOR (Tree, q_{rand})	12. then q_{new} is collision; return true;
6. NEW_CONFIGURATION (q_{near}, q_{rand})	13. else if $P(q_{new}) < \beta_{free}$
7. While(Dis (q_{new}, q_{goal}) < Threshold $t > T_{max}$)	14. then q_{new} is free ; return false;
	15. else ExactCollisionCheck (q_{new});

The K multivariate Gaussian mixture components of GMMs is described as below.

$$P(x|\sigma) = \sum_{k=1}^K \mu_K(x|\sigma_k) \quad (1)$$

where μ_k is Gaussian component weight and is satisfied $\sum_{k=1}^K \mu_k = 1, \mu_k \geq 0$. $\psi(x|\sigma_k)$ is the probability density function of k independent Gaussian distributions, σ_k is parameter vector for the distribution. Generally, the maximum likelihood is used to estimate the parameter of GMMs. Finally the log-likelihood converges to a maximum value by multiple Expectation-Maximization (EM) iterations.

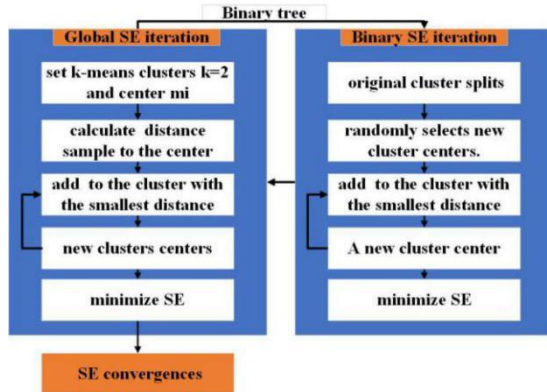


Figure 2. The Greedy K-means algorithm.

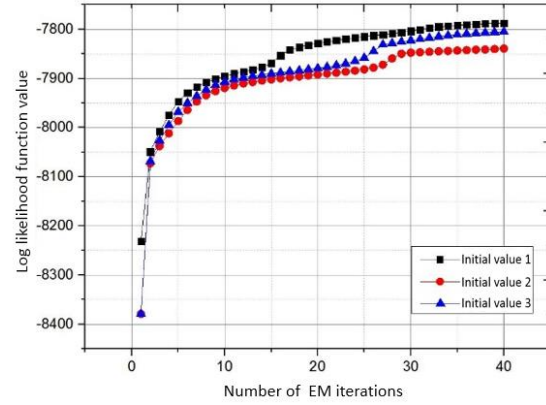


Figure 3. EM convergence of different initial values

3.1 Greedy K-means for EM initialization

The iterative result of the EM algorithm is greatly influenced by the initial parameter, so the choice of initial value is crucial to the quality of the training model. Models with large k values can fit the model more accurately, but we need to train more data, which increases the computational cost and even causes over fitting. With the least square error SE as the evaluation index, a greedy SE iterative algorithm is proposed to select the appropriate cluster number k for K-means. As we can see, Figure 2 presents the greedy K-means algorithm combined with two parts. It splits down in the form of a binary tree and iterate until the SE converges, and then get the most suitable number of Gaussian components. Figure 3 is three groups of initial values obtained by K-means algorithms which shows that EM can converge stably only with tiny fluctuations.

$$SE = \sum_{i=1}^K \sum_{X \in C_i} |X - \bar{X}_i|^2 \quad (2)$$

3.2 Gaussian Sample

To increase the probability of sampling near obstacles, using Gaussian distribution sampling strategy with adjustable variance to obtain a valid sample set, within a certain range of the target region for different working environments with different complexity. Table 2 presents the Gaussian sample algorithm that samples valid points near obstacles.

Table 2. Gaussian sample near obstacles.

1. loop	5. then $V \leftarrow V \cup \{c1\}$
2. Rand Sample (q_{rand})	6. else if $c2 \in C_{free}$ and $c1 \in C_{free}$
3. $c2 = \phi(q_{rand}; \sigma)$	7. then $V \leftarrow V \cup \{c2\}$
4. if $c1 \in C_{free}$ and $c2 \in C_{free}$	8. else discard $c1$ and $c2$

Defining a multivariate Gaussian distribution function in an n -dimensional configuration space as below.

$$\phi(c; \sigma) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{c^2}{2\sigma^2}} \quad (3)$$

Where σ is the standard deviation of the multivariate Gaussian distribution, indicating the width of the Gaussian sample. The σ also means when approaching the obstacles, the probability of sampling is greater. Using RRT, we do motion planning based above sample strategy in 2D space for easy visualization. As Figure 4 shows, the blue boxes are obstacles, the red lines indicate the RRT branches, and the green line is the final planning path. Figure 4. (a-b) sample from GMMs-free, corresponding to Gaussian sample sets with standard deviations of 0.25 and 2.5. Figure 4. (c-d) are the contour maps of the corresponding Gaussian mixture models, the brighter areas indicate a larger sampling probability. We can see that the size of the standard deviation corresponds to the size of the sampling space. Figure 4. (e-i) show the planning effects of RRT in the scene of large free space. The corresponding sampling strategies are uniform sample, GaussianValid based sample, GMMs-free based sample, GMMs-free combined with the 5,10 standard deviation of Gaussian sample. Figure 4. (j) is the corresponding planning time. The result shows for this “narrow scene”, RRT using the GMMs-based sampling strategy with the smallest standard deviation is the shortest planning time. Our method can significantly reduce the number of collision checks by narrowing the search space and then shorten the planning time. We also call GMMs-free learned with Gaussian sample sets as GGMMs-free.

4. GMMs-based Collision Checker

Using the learned GMMs of the obstacle region distribution in the configuration space(GMMs-obs), quickly determines whether the configuration collides with the obstacle or not, and then the kinematic-based accurate collision detection is performed on the ambiguous sampling points of the prediction results. Finally, accurate collision detection based on positive kinematics is required for the generated path to ensure the safety and feasibility of the manipulator movement.

Calculate the probability P of the new sample point belonging to the GMMs-obs.

If $P < \beta_{free}$, the robot will not collide with the obstacle in this configuration;

If $P > \beta_{obs}$, the robot will collide under this configuration;

If $\beta_{free} < P < \beta_{obs}$, we use accurate methods such as AABB to check a collision.

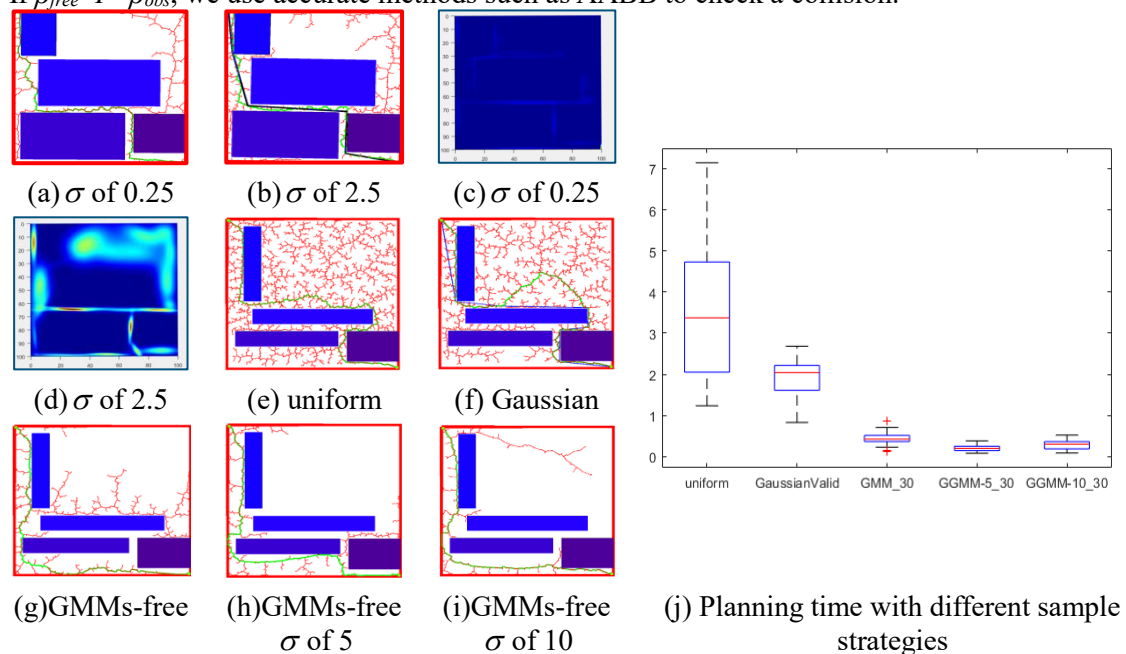


Figure 4. GMMs trained using different variance Gaussian sampling

5. Result

In this paper, the UR5 robot is used in different simulation environments, and the algorithm is verified by ROS and Gazebo. We use Octree map combined with FCL library for exactly collision detection.

In order to prove the performance of the GMMs-based sampling strategy and collision checker for higher-dimensional motion planning, it is compared with kinematic-based collision checker and uniform random sampling methods in various sample-based motion planning methods. The UR5 robot is used to perform motion between specified positions in four different working scenes as Figure 5 shows. Table 3 shows the results of 100 experiments that the average planning time used by GMMs-based motion planning is significantly shorter than the origin method in the four scenes.

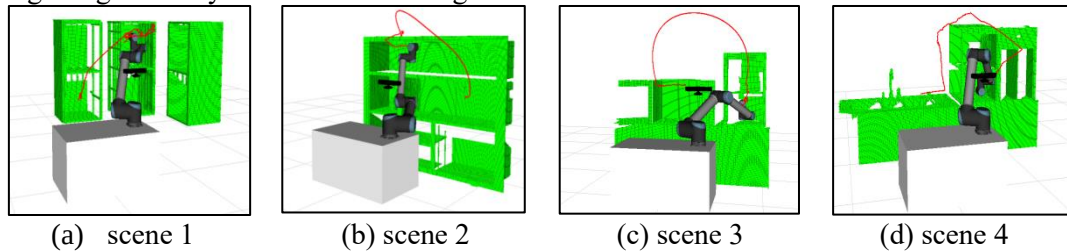


Figure 5. The effects of 6-DOF robot programming in four scenes respectively.
(The red lines are planned trajectories.)

6. Conclusion

In order to improve the efficiency of the sampling-based motion planning algorithm, this paper proposes an adaptive sampling strategy and a fast collision checker based on Gaussian Mixture Models. In order to improve the fitting precision of the models, the greedy K-means method is used to initialize the EM parameters. In order to effectively solve “narrow corridor” problem, GMMs is combined with Gaussian sampling of adjustable variance, which can remarkably reduce the number of collision checks. Following this method, the whole experimental results show that sampling motion planning method based on GMM is obviously faster than previous.

For future work, we will improve the accuracy of the GMM and apply this method to continuous collision checking.

Table 3. Average time in the four scenes with different methods

Average time(s)	Scene 1		Scene 2		Scene 3		Scene 4	
	origin	GMMs	origin	GMMs	origin	GMMs	origin	GMMs
RRT	79.76	25.67	79.75	28.65	79.71	27.13	79.74	30.12
RRT-Connect	31.39	16.24	26.30	16.04	19.14	10.03	23.62	11.42
LAZY_RRT	81.42	33.61	79.53	29.87	79.85	35.20	70.49	27.80

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