Obstacle Avoidance Trajectory Planning for Gausian Motion of Robot Based on Probability Theory

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*Abstract*—When the robot’s movement has process noise, or its closed-loop feedback sensors have specific observation errors, the robot will present significant uncertain movement. The non-deterministic movement state is described by the Gaussian distribution which is widespread in nature. The probability theory combing with the robot’s linear control and Kalman filter estimation is used to plan the trajectory and evaluate the A priori probability distribution. Liner control method is used in combination with Kalman filter to establish error model of Gaussian motion system. Then, all feasible trajectories are assessed by the Gaussian motion model by calculating the probability of avoiding obstacles and arriving at the target. For the optimal trajectory planning, spline method is used to calculate a set of feasible paths. Theoretically, all those trajectories can get the aim point and avoid the obstacles. But for the uncertainty of the robot’s behavior, the robot still has the probability of collision and miss the target. Through Gaussian movement prior probability estimates, the trajectory with the maximum probability value is the optimal on under the non-deterministic Gaussian motion state of the robot.

Keywords—Gaussian motion, robot, probability, trajectory planning

# Introduction

In this experiment, on the basis of the linearization of the robot model, the observation sensor Kalman filter is used to estimate the error probability of the robot moving along the predetermined trajectory in advance, and the expected value of the point seat probability and the possible error on the predefined probability are expressed by covariance. Generate a probability ellipse for the probability distribution after each motion. And calculate the collision probability with obstacle after each movement, so as to get the collision probability of the whole track. On this basis, the spline method is used to generate multiple trajectories, and the collision probability of each trajectory is calculated. Finally, the trajectory with the lowest collision probability is selected as the optimal trajectory.

In this experiment, the robot trajectory, motion control cycle, trajectory analysis based on Bayesian theory and iteration of sensor error distribution are combined to quantitatively calculate the actual motion success probability of the robot. The experimental results show that the trajectory planning method based on probability theory can effectively estimate the error distribution, variation trend and success probability of robots reaching the target point in each movement period.

# Relate Work

At present, most research on trajectory planning methods of robotic systems are based on the deterministic assumptions of the system, and there are many excellent results[1-3].In the research of robot non-determinism, Bry[4] added system non-determinism to the node generation process of the random expansion tree. Each time a new node is generated, the Monte Carlo method is used to test the variance probability of the new node and carry out trajectory planning. Toit[5] et al. combined LQR control with Kalman filter in the robot control system, and used the rolling time domain method to reduce the movement deviation of the robot system. Sun[6] et al. applied multi-core and multi-threaded programming technology to apply Toit's LQG non-deterministic sampling optimization method to real-time calculations, and simulated the real-time trajectory planning of medical probes and mobile robots.

# System definition

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# Priori Estimation of Trajectory Error Distribution

## Kalman filter estimation

Due to the errors in the process of robot movement, the position deviation between the actual output of the system and the system instruction is subject to Gaussian distribution in each control cycle. And because the observation system also has observation noise subject to Gaussian distribution, the deviation state of robot trajectory cannot be accurately reflected. Therefore, moving Kalman filter can effectively estimate the position of the robot. The principle of the Kalman filter is not introduced here. In this experiment, Kalman filter is used to estimate the error in the process of gaussian trajectory planning.

# Collision probability calculation

## Gaussian motion probability ellipse representation

Through the iteration of the trajectory modeling and estimation process in Section 2, the normal distribution variance of the robot trajectory points in each control cycle is obtained. The probability ellipse can be used to represent the distribution of variance. Assume that the covariance matrix at the trajectory point P is Ti. As shown in Figure 2, in Figure 2, random points that obey the normal distribution with an expected variance of P are distributed, and each random point represents a possible position of a robot.

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描述已自动生成

1. Probability Ellipse Generation Process

## Obstacle avoidance probability calculation

When the robot performs Gaussian motion near an obstacle, as long as the probability ellipse intersects the obstacle, the robot may collide with the obstacle. From the principles of mathematical statistics, this probability will be reflected in repeated trials of the same trajectory.

For the same planned trajectory, the same obstacle, and the same control period, collisions sometimes occur after multiple tests, sometimes not. When the test sample tends to infinity, the ratio of the number of collisions to the total number of tests will be infinitely close to a certain probability value. The method of obtaining this probability value.

## Trajectory optimization method

In order to plan the optimal trajectory of the robot's Gaussian motion according to the robot's motion error characteristics and sensor error characteristics before the robot moves, some autonomous optimization strategies can be used, such as genetic algorithm, random extended tree (RRT) and other methods to get a lot of A predefined trajectory to reach the target point. Then use the method based on probability theory described in Section 3.2 to evaluate the probability of success of each trajectory.

The method of autonomous trajectory optimization will not be repeated in this article. What needs to be explained is: According to actual simulation research, it is not suitable to use optimization methods such as RRT\* for pre-defined trajectory planning while applying the method in this paper. Because these methods have their own optimization strategies, the resulting set of predefined trajectories is the result of screening through this optimization strategy. On the one hand, these trajectories cannot uniformly cover the robot state space due to optimization screening, and on the other hand, the optimization strategy cannot guarantee consistency with the safety of the robot's Gaussian motion.

As shown in Figure 5, if an optimization method such as RRT\* is used to plan a set of predefined trajectories to reach the destination point, due to the optimization strategy of the RRT method itself, in order to obtain the shortest trajectory path, the trajectory will bypass the obstacle in a closer way obstacle. But these trajectories will be the probability ellipses and obstacles of the method in the Gaussian motion of the robot.

# Collision probability calculation

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# CONCLUSION

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##### Acknowledgment *(Heading 5)*

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