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Model of Obstacle Avoidance on Hard Disk Drive Manufacturing with Distance Constraint

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***Abstract*—**Obstacle avoidance is the one key for the robot system in unknown environment. The robots should be able to know their position and safety region. This research starts on the path planning which are SLAM and AMCL in ROS system. In addition, the best parameters of the obstacle avoidance function are required. In situation on Hard Disk Drive Manufacturing, the distance between robots and obstacles are very serious due to the manufacturing constraint. The simulations are accomplished by the SLAM and AMCL with adaptive velocity and safety region calculation.

***Keywords*—**Obstacle avoidance, simultaneous localization and mapping, adaptive Monte Carlo localization, KLD sampling.

I. Introduction

THIS research is the obstacle avoidance on Hard Disk Drive manufacturing which has distance constraint. The purpose of Hard Disk Drive manufacturing is the automation system to increase capability on manufacturing process. The minimum distance is 0.5 meters and the robot width is 0.5 meters.

Many researchers studied localization, path planning and obstacle avoidance. Lima and Ventura studied about the parameter improvement for localization optimization [1]. Li et al. used adaptive particle for robot localization by sampling [2]. Zhang et al. studied the efficiency improvement by selecting the good sampling. The results illustrate good performance [3]. One of important sections for robot control is the path planning. Koziol et al. studied the autonomous path planning by using analog very large scale integrated (AVLSI) which is processing by IC [4]. Hildebrandt et al. studied the real-time path planning in unknown environment [5]. Devaurs et al. use RRT for optimal path planning and the results show that AT-RRT is better than T-RRT [6]. Wan et al. use Gaussian process (GPR) for estimation of the robot movement and they can improve accuracy of robot position movement [7]. Banfi et al. studied time adjustment for path planning in 2 dimensions [8]. Petrick and Federico studied the robot motion such as leg motion and circular motion for path planning but their research used the open-loop control. Their results can be improved in future work by using closed-loop control [9]. In addition, the main feature for robot movement is obstacle avoidance which is function for robot decision in environment. Luo and Kuo studied the obstacle avoidance in dynamic system on factory by using 3D sensor for object detection in attractive vector and repulsive vector. Testing result is good for obstacle avoidance [10]. Yang et al. focused on the nonlinear design system based on nonholonomic constraint. If they test model on real system, the system will have more reliability [11]. Kim and Chwa used fuzzy system for obstacle avoidance. The results show that fuzzy type 2 looks better than fuzzy type 1 on both model simulator and real systems [12]. Tanaka et al. studied the localization on snake robot using laser range finder. They calculated the reduction of cost function on unknown environment with good performance [13]. Flacco and Luca calculated the distance between robot and obstacle by using camera on complex environment [14]. From the previous research, many researchers focused on the robot movement on environment in effectively. The development for robot is important in future.

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II. Robot Simulator System

A. Operating System

This research used Robot Operating System (ROS) in Kinetic Kame distro and Ubuntu 16.04 for operating system. The ROS is the popular system for robotic developers because it has a lot of robot library and tools for development. The languages are Python and C++.

B. Unified Robot Description Format (URDF)

URDF is the file in ROS which is on XML format. This research used URDF for robot structure such as chassis, wheel, and sensor. Link element and joint element are the structure of URDF. Link element is component on each part of robot in simulator. This research created the chassis, left wheel, right wheel, camera, and laser range finder as link. Joint element is the connection between link elements. The chassis and wheel are connected in continuous joint type for continuous rotation. Camera and laser range finder are connected with chassis in fixed joint type.

III. Path Planning

A. Simultaneous Localization and Mapping (SLAM)

SLAM is one of the tools in ROS which is "gmapping" tool. It used for robot position estimation on environment in map at that time. Main feature of SLAM is probability on unknown environment. The error from map and estimated position are correlated. SLAM process is divided in 2 sections. Section I is motion model which uses the previous robot position (X_{k-1}) and robot's control (U_k) for robot position estimation (X_k) in next state as shown in (1):

$$x_k = f(x_{k-1}, u_k) \tag{1}$$

Section II is the observation model which uses robot position estimation (X_k) and map (m) for observation value (Z_k). Equation (2) shows the observation value function.

$$z_k = h(x_k, m) \qquad (2)$$

The concept of SLAM is robot position estimation system due to uncertainty of robot position. The Gaussian distribution is taken into function for probability of robot position. The Gaussian function is shown in (3):

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/(2\sigma^2)} \qquad (3)$$

B. Adaptive Monte Carlo Localization (AMCL)

AMCL is the probability of localization of robot with particle filter. In odometry localization, it can used for robot position estimation but the robot cannot know position itself in map. In case of AMCL, the robot can know position itself in map. The Bayesian filtering is shown in (4) where $x_t = \{x, y, \theta\}$ is robot position and $z_k = \{z_t^1, z_t^2, \ldots\ldots, z_t^k\}$ is observation vector.

$$\overline{bel}(x_t) = \int p(x_t \mid u_1, x_{t-1}) bel(x_{t-1}) dx_{t-1} \qquad (4)$$

$\int p(x_t \mid u_1, x_{t-1})$ is the probability in motion model.

$$bel(x_t) = \eta\, p(z_t \mid x_t, m)\overline{bel}(x_t) \qquad (5)$$

$p(z_t \mid x_t, m)$ is the probability in observation model. η is Bel's constant. In addition, the sampling is the one of process in AMCL which is used for selection the good sampling. The ROS have KLD-sampling for AMCL. Good estimation in KLD-sampling is derived by Wilson-Hilferty equation.

$$n_x = \frac{k-1}{2\varepsilon}\{1 - \frac{2}{9(k-1)} + \sqrt{\frac{2}{9(k-1)}} z_{1-\delta}\}^3 \qquad (6)$$

TABLE I
DIFFERENCE BETWEEN SLAM AND AMCL

Item	SLAM	AMCL
1	Define robot position	Define robot position
2	Create new map	Use created map
3	Changeable start point	Fixed start point
4	Slow processing time	Fast processing time

IV. OBSTACLE AVOIDANCE

One of the main functions for robot movement in environment is the obstacle avoidance. The detection region and safe region are concerned.

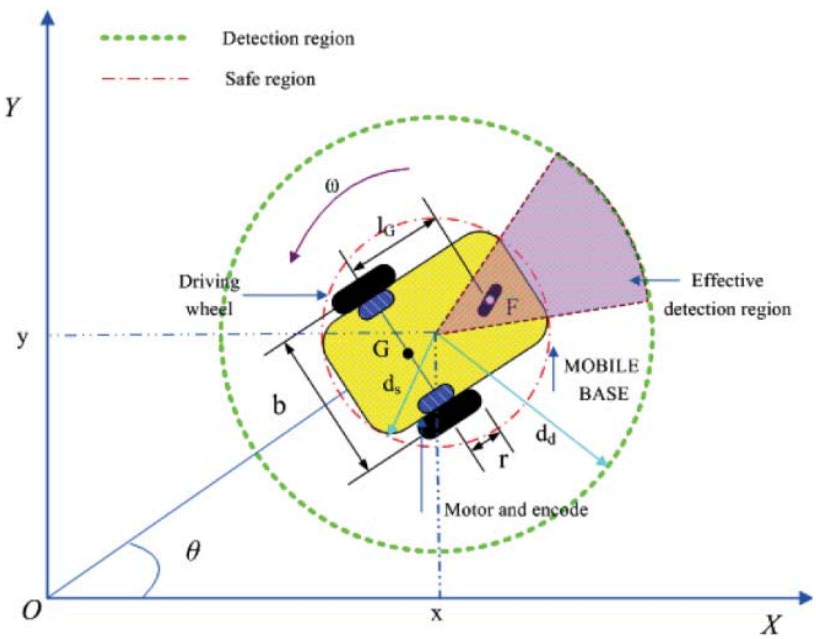

Fig. 1 Robot and region in X-Y plane [11]

Fig. 1 shows the robot and region in X-Y plane. The red circle is the safe region which is defined from robot size. The green circle is the detection region which is the region for sensor detection. The obstacle avoidance function is shown in (7):

$$V_{ob} = (\min\{0, (L_{rod}^2 - d_d^2)(L_{rod}^2 - d_s^2)^{-1}\})^2 \qquad (7)$$

V_{ob} is in range between 0 and 1 where d_d is radius of detection region circle and d_s is the radius of safe region circle. The radius of detection region is more than the radius of safe region in every time. L_{rod} is the distance between obstacle and robot where obstacle position is (x_o, y_o) and robot position is (x_i, y_i).

$$L_{rod} = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \tag{8}$$

V. Methodology & Results

The methodology of this research was started in robot structure with 0.5 meters width and 0.8 meters length. Then, the laser range finder is set to be 2D sensor for distance detection. The environment is created in Gazebo which is simulator in ROS. SLAM is the first section for testing. In simulation, user needed control robot in manual for map creation. Processing time is about 20 minutes to make map from SLAM as created environment. Processing time in SLAM depends on environment. After that, AMCL is used for obstacle avoidance testing by using created map from SLAM.

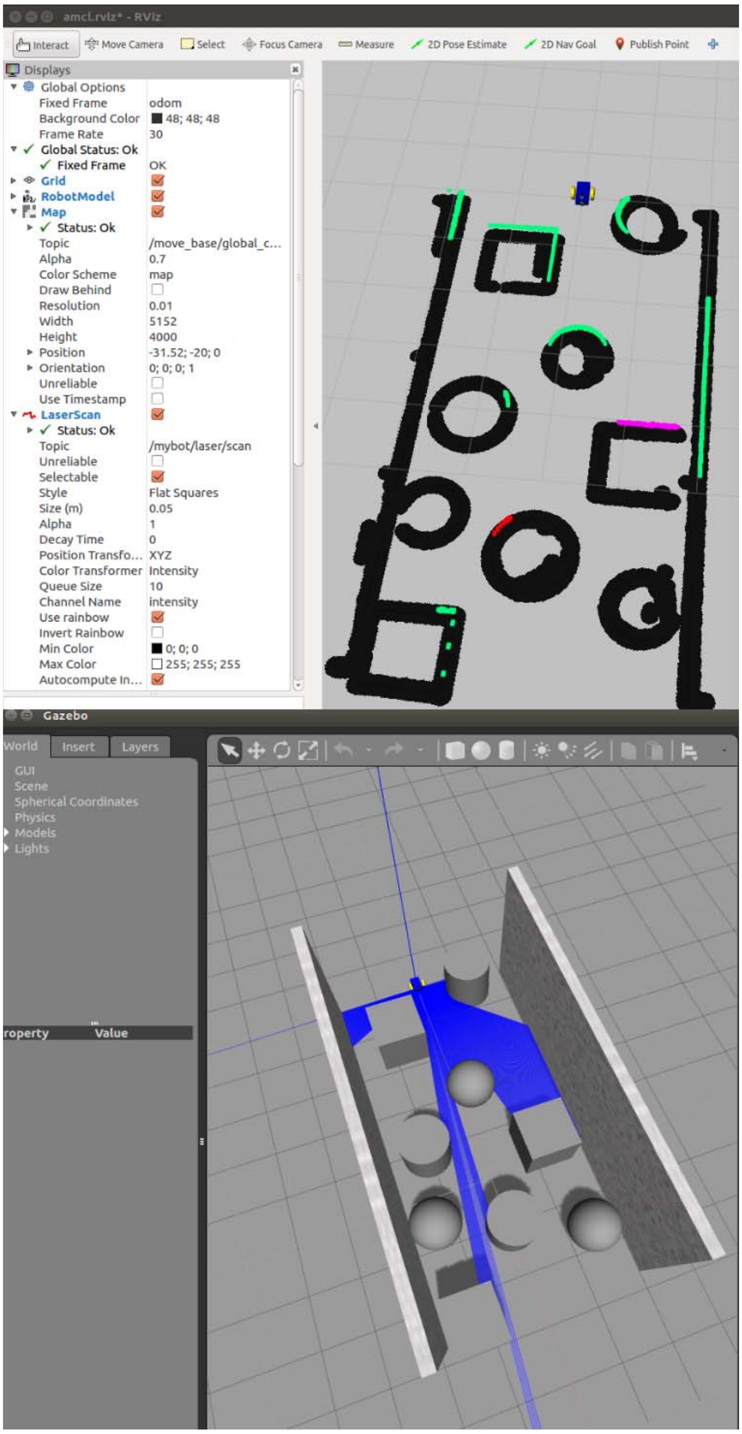

Fig. 2 Robot in environment on Gazebo and RViz

In ROS, Gazebo is simulator which shows the world as human sees but RViz is the visualization of robot. This model shows that the robot can move fast without crashing on obstacle with 1.0 m distance constraint between robot and obstacle.

Table II is the results from 0.5 m distance constraint gap between robot and obstacle.

TABLE II
SIMULATION RESULTS ON 0.5 M DISTANCE GAP

Item	Condition	Start point to target point	Processing time (min)	Obstacle avoidance
1	Fix velocity	Fail	infinity	Fail
2	Adaptive velocity	Pass 3/5	5.20	Pass
3	Adaptive velocity with safety region adjustment	Pass 5/5	3.42	Pass

From Table II, the fix velocities do not work due to 0.5 m distance constraint and robot cannot stop immediately when robot moves closely to obstacle. In condition 2, the robot can move without any crashing but robot cannot move to target point. Robot moves around body itself. The best condition is the adaptive velocity with safety region adjustment.

VI. CONCLUSION

From model of this research, the best condition for 0.5 gap constraint from Hard Disk Drive manufacturing is adaptive velocities with safety region adjustment. The robot can do autonomous movement in map by self with minimum processing time.

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