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Path planning of an autonomous mobile robot considering region with velocity constraint in real environment

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Abstract: Recently, various autonomous mobile robots are tried to drive in the real world in many researches or competitions. In this case, it is very important for the robot to identify the self-position and orientation in real time. Therefore, we apply a localization method based on particle filter to the autonomous robot. Moreover, in order to improve the safety of autonomous locomotion, we improve the algorithm for path planning and trajectory generation so that it can consider the regions with the limitations of maximum velocity. In order to demonstrate the validity of the proposed methods, we will participate in the Real World Robot Challenge 2010.

Keywords: Autonomous robot, trajectory generation, localization

1 Introduction

Recently, many researches related to the autonomous mobile robot have been reported. Various competitions for autonomous robots have also been held to validate the autonomous locomotion functions in the public environment (see e.g [1, 2, 3, 4]).

We have participated in RWRC since 2007 (see [5, 6, 7]), to validate our autonomous robot system in the real environment. In RWRC, the robot has to move within the general pedestrian paths including general people, unicycle and etc. Therefore, unlike the other competitions, the robot is required not only the autonomous locomotion functions but also the safety of the autonomous locomotion. In [7, 8], we proposed a trajectory generation method considering "The Region with Velocity Constraint" (RVC) to improve the safety of the autonomous locomotion. The RVCs are the region where the velocity of the robot is restricted to the predefined velocity, and introduced to around the hazardous regions by the operator. The trajectory generation method in [7, 8] generates the trajectory avoiding the hazardous regions or reducing the risk in the hazardous region by constraining the velocity according to RVCs. However, there is a limitation that the method cannot consider the unknown or dynamic obstacles (e.g. humans and unicycles), because it generates the trajectory based on the predefined map.

Moreover, in [6], we estimate the position of the robot from the odometry data and GPS data by using the extended kalman filter. In general, if the satellite condition is good, we can obtain the accurate position data from GPS by using differential GPS or Real time kinematic GPS. However, since there are many obstacle (e.g. trees, buildings) within the course of RWRC, we could not obtain the GPS data with enough accuracy for correcting the position of the robot at many locations. Therefore the localization method fully depends on GPS is not suitable for such environment.

In this study, we improve the trajectory generation method so that it can consider not only the registered obstacles but also the unknown or dynamic obstacles, while considering the RVCs as in [7, 8]. Moreover, we improve the accuracy of the localization by combining gyroodometry and particle filter based localization method. We validate the improved system in RWRC2010. The contents of this paper are as follows. In Section 2, we improve the trajectory generation method, and in Section 3, describe localization method used in this paper. In Section 4, we show the developed robot system and show some experimental results. We conclude this paper in Section 5.

2 Trajectory generation with RVCs

As mentioned before, the trajectory generation method[8] considers RVCs. The RVCs are the region where the velocity of the robot is restricted to the predefined velocity, and introduced to around the hazardous regions by the operator in advance. For example, the hazard areas where the robot is not allowed to enter (e.g steps, neighborhood of the pond) are registered as the regions with velocity constraint $v_{max} = 0$, and the area where the robot should reduce the velocity (e.g rough road, narrow street) are registered as the regions with the velocity constraint $v_{max} < 1.0$ (see Fig. 1). Since the robot plans the trajectory according to the registered information, it is expected that the predicted hazard can be avoided. (e.g. reduction of the shock if the robot collides an obstacle, passing smoothly at the complicated narrow road)

In [8], the gird map including the RVCs, the known obstacles and waypoints information is given in advance, and is used for trajectory generation. There-

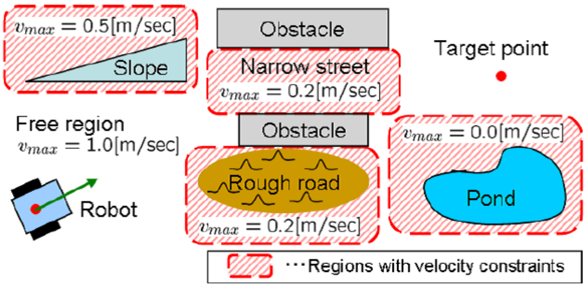
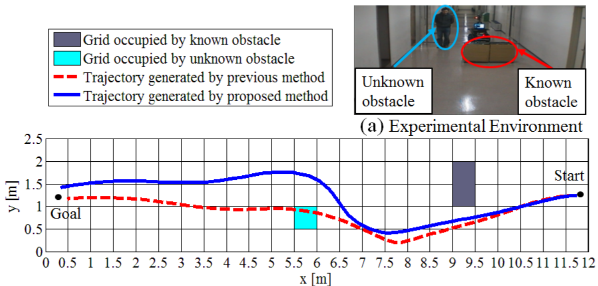


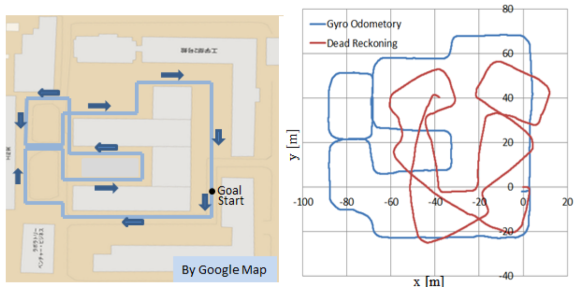
Fig.1 The concept of RVCs



(a) Experimental Environment

(b) Result of the trajectory planning

Fig.2 Example of generated trajectory



(a)Running Trajectory (b)Estimated Trajectory

Fig.3 Example of raw odometry and gyroodometry

fore, the generated trajectory avoids only the registered obstacles. However, since there are unregistered obstacles (e.g. humans and bicycles) in the real world, the robot also has to avoid such dynamic obstacles. To this end, we modify the grid map used in trajectory generation so that it can take into account unknown and dynamic obstacles. More precisely, we generate a new map in each sampling time by combining the priori grid map and current obstacle information obtained from sensor. Then the trajectory is generated based on this map in each sampling period.

Fig. 2 shows an example of the trajectory generated by two methods. Fig. 2(a) shows the experimental settings. In Fig. 2(b), a red line shows a trajectory generated by the past work and a blue line shows one by the method described in this section. From this figure, we can see that the trajectory, generated by past work, collides with the unknown obstacle (i.e. an unregistered obstacle). Therefore, since we have to use external obstacle avoidance function to apply this trajectory to the real robot, the optimality of the trajectory might be reduced. On the other hand, the proposed method generates the optimal trajectory while avoiding every obstacles.

3 Localization method

The localization method used in this study can be divided into two part: gyroodometry and particle filter based localization. First the accuracy of the odometry is improved by using gyroodometry[10] based on the fiber optic gyro (Sec. 3·1). Second, the gyroodometry data is corrected by the particle filter based localization method using the priori map and current obstacle information obtained from a laser range scanner (Sec. 3·2).

3·1 Gyroodometory using optic fiber gyro

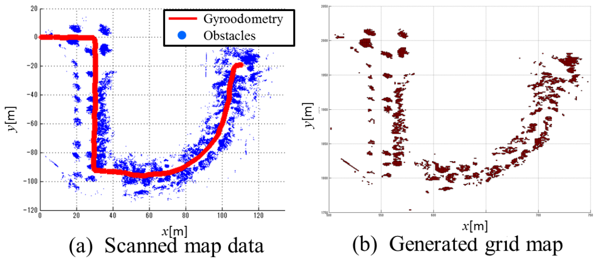
The gyroodometry is a method estimating a pose of the robot from the odometry and gyro sensor data. In this study, we use the 1-axis optic fiber gyro, and gyro sensor data is used for yaw rate.

Fig. 3 shows one of our experimental results. In this example, the robot is operated by manually on the campus road at Kyoto University from start position to goal position according to the direction of arrows(about 500[m]) as shown in Fig. 3(a). Fig. 3(b) shows the trajectory of the robot estimated by raw odometry and gyroodometry. Note that, the start position and goal position on the map were set at $(x, y) = (0, 0)$. From Fig. 3(b), it can be see that the gyroodometry shows much better result compared with the raw odometry. In fact, the error between start and goal position is bounded less than 2[m].

3·2 Pose correction by using particle filter

In order to correct the gyroodometry data, we use a Monte Carlo Localization(MCL) method[9]. MCL is a method for estimating the pose of the robot based on Particle Filter(PF). In this study, we use a priori 2D grid map and range data from a laser range scanner for MCL. The outline of our localization method is as follows: First, the pose of the robot in each particle are calculated based on gyroodometry. Next, the range data obtained from LRF is converted into global map based on the pose of the robot in each particle. Then the weight of each particles are calculated by comparing the priori grid map and the converted obstacle map in each particle. Finally, resample the particles according to their weight. By iterating above procedure in each sampling period, the pose of the robot is estimated.

The priori map used in MCL is generated according to the following procedure. First, we obtain 3D range data from the 2D laser range finder mounted on a pitch rotating platform. In RWRC, since many dynamic obstacles(e.g. humans, unicycles) are exist, much noise is included in the lower parts of 3D range data. In order to reduce affection by noise, we use only the 3D range data in the part higher that 2[m] height. The partial 3D range data is converted into global map according to gyroodometry and converted



(a) Scanned map data (b) Generated grid map

Fig.4 Example of the priori map

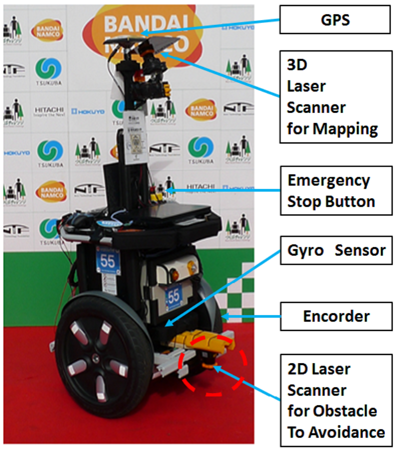


Fig.5 System configuration of the developed robot

into 2D map with orthogonal projection to ground plane(e.g. Fig. 4(a)). Then, the map is saved as the grid map to reduce the memory (e.g. Fig. 4(b)). In the case of Fig. 4, Fig. 4(b) is used as a priori map in PF based localization.

Note that, as mentioned in Sec. 2, this priori map is used for trajectory generation as well. For trajectory generation, waypoints, RVCs and current obstacle information are included to this grid map in each iteration,

4 Experiments

The trajectory generation method in Sec. 2 and the localization method in Sec. 3 are applied to the developed robot as shown in Fig. 5. The developed robot equips a GPS, a fiber optic gyro, a 3D laser scanner, encoders, an emergency stop buttons and a 2D laser scanner to detect obstacles. Note that the software is implemented by using RT-Middleware[11].

In order to verify the developed system, we execute the following three experiments in RWRC2010.

Experiment 1 Verification of the performance with the fiber optic gyroodometry described in Sec. 3·1

Experiment 2 Validation of trajectory generation method described in Sec. 2

Experiment 3 Verification of particle filter based localization method described in Sec. 3·2

In RWRC2010, as shown in Fig. 6, the course is divided into to two parts: the trail course (about

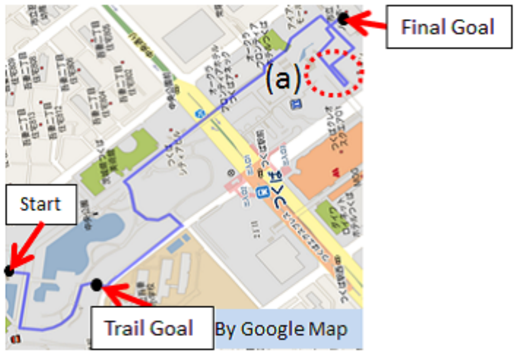


Fig.6 The full course of the RWRC2010

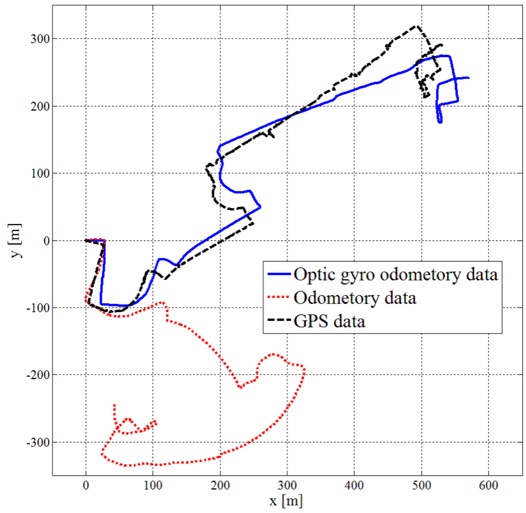


Fig.7 The estimated trajectory in Experiment 1

240[m]) and full course (about 1100[m]). Experiment 1 is done in the full course, and Experiment 2 and 3 are done in the trial course, because of the restriction of time in RWRC2010.

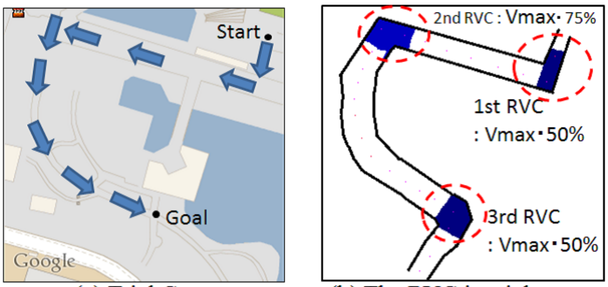
4·1 Experiment 1

Fig. 7 shows the experimental result of Experiment 1. In this experiment, the robot is operated manually. From Fig. 7, it can be seen that the gyroodometry reduces the estimation error compared with the raw odometry data. However, compared with the course in Fig. 6, the estimated trajectory differs from the global map as the robot moves long distance. Especially, we can see that the trajectory curves slightly even in the straight line course. This is mainly because the drift of the gyro sensor. Therefore, although the gyroodometry is enough accurate for a short course, the correction by PF is necessary to run the long course.

4·2 Experiment 2

In Experiment 2, the RVCs are set as shown in Fig. 8(b). The robot moves autonomously according to the trajectory generation method described in Sec. 2. The gyroodometry data is used for localization (i.e. PF is not used in this case).

Fig. 9 shows the translational velocity of the robot



(a) Trial Course (b) The RVC in trial course

Fig.8 RVCs for the trial course

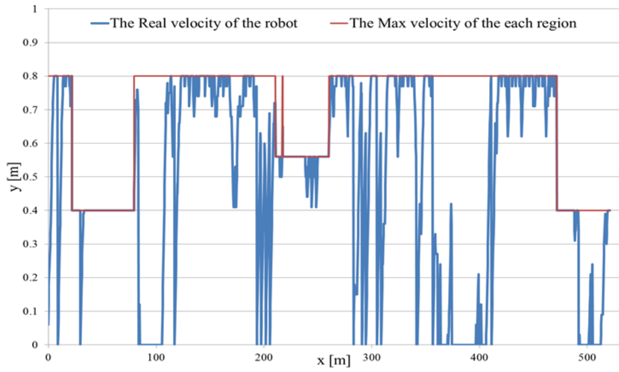


Fig.9 Translational velocity profile in Experiment 2

in Experiment 2. In Fig. 9, a red line shows a admissible maximum velocity of the robot according to the registered RVCs information. From Fig. 9, we can see that the robot reduces the velocity before moving into the each RVC enough, and satisfies the velocity constraint of each RVC. Moreover, the robot could reach goal position of the trial course without colliding any obstacle, even though there were many unknown and dynamic obstacles. Therefore, it can be said that the improvement of the method works correctly.

4·3 Experiment 3

Fig. 10 shows the experimental result of the Eexperiment 3. In Fig. 10, a green line shows a trajectory when the priori grid map is generated, a red line shows a trajectory estimated by the gyroodometry, and a blue line is a trajectory estimated by the particle filter. In other word, a green line is a "true" trajectory in this case. From Fig. 10, we can see that the trajectory estimated by gyroodometry differs from the one in the priori map (i.e. a green line). On the other hand, the trajectory estimated by PF agrees well with the green line. Therefore our particle filter based localization method estimates the position correctly.

5 Conclusions

In this study, we improved the trajectory generation method proposed in [8] and the localization method for an autonomous robot in the real environment. We participated in RWRC2010 to validate the developed system, and some experimental results showed that

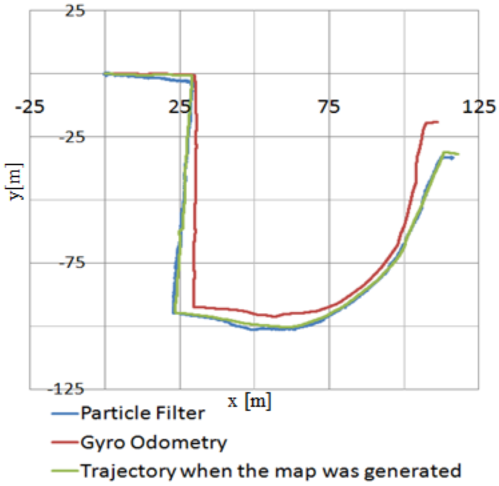


Fig.10 The estimated trajectory in Experiment 3

the validity of our system. One of the future works is to predict motion of the dynamic obstacles, and improve the safety of the autonomous locomotion by considering their information.

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