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Moving Obstacle Avoidance for the Mobile Robot using the Probabilistic Inference

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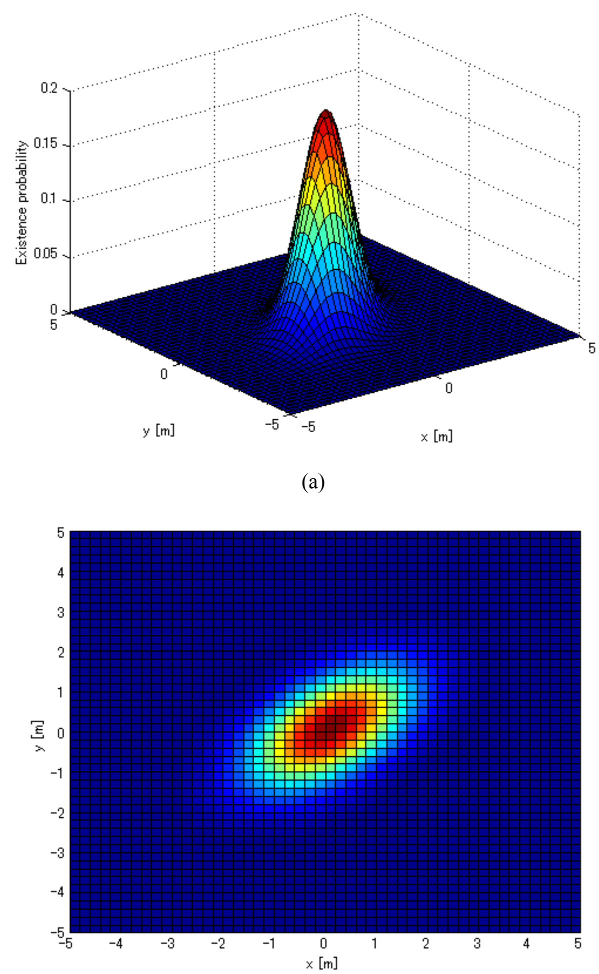
***Abstract* - In this paper, we present a motion planning algorithm using the probabilistic inference for the mobile robot. This study aim is for the mobile robot to avoid the moving obstacle and to reach the target position. The proposal algorithm consists of three steps. In the first step, robot system predicts the trajectory of the moving obstacle. Prediction is performed as what the moving obstacle follows to tangential direction by the proposal algorithm. In the second step, robot system calculates the prediction region of the moving obstacle. Mathematical model that is based on the probability density function of two-dimensional normal distribution is used in prediction region. In the third step, robot system plans the mobile robot motion. The potential field method is used in the motion planning for the mobile robot. The proposal algorithm was investigated by simulations in order to be effective. By simulations, we tested whether the mobile robot can avoid the moving obstacle and reach the target position. The mobile robot can avoid the moving obstacle was confirmed by simulation results.**

Index Terms – Motion planning. Probabilistic inference. Mobile robot. Moving obstacle avoidance.

I. Introduction

In recent years, various mobile robots are developed to use in offices, factories, and so on. The indoor environment such as the Office is the place where a human being works. Therefore, the mobile robots working in the indoor environment are asked for the capability not to block human's work. The mobile robots in the practical use so far have realized the obstacle avoidance for fixed obstacles. In case that the mobile robot can predict the position of moving obstacle, it can avoid the moving obstacle. However, it is often difficult to predict the next position of the moving obstacle. The obstacle avoidance about the moving obstacle which does not know where to move is still a study phase. The mobile robots in practical use stop at the current position to avoid colliding with the human. And they wait until human going away. It is not an efficient thing that the mobile robots wait during work, because the mobile robots will stop work while the mobile robots wait. If the mobile robots could avoid human, the efficiency of work could become good and the spread of the mobile robots could be promoted.

This study aim is for the mobile robot to avoid the moving obstacle which does not know where to move and to reach the target position. Since motion of the moving obstacle may change, the moving obstacle position cannot be presumed certainly. In other words, trajectory prediction of the moving obstacle does not have a method other than probabilistic inference. Therefore, we focus on the density function of the probability density function of the two-dimensional normal distribution.



(a)

(b)

Fig. 1 Graph of the probability density function of two-dimensional normal distribution. (a) Side view, (b) View from above.

Figure 1 shows the graph of the probability density function of the two-dimensional normal distribution. It represents a high probability that the higher the height of the graph. The moving obstacle is calculated the existence probability by the proposal algorithm in the next time. The calculated existence probability of the moving obstacle is plotted as a three-dimensional graph as shown in Fig.1. The mobile robot system plans the motion which avoids the position where probability is high as shown in Fig.1. Section III describes these methods in detail.

In the next section, related work is described about obstacle avoidance. The proposal algorithm is presented in section III. Section IV described about the simulation which used the proposal algorithm. Finally the paper ends with the conclusion in section V.

II. Related Work

A variety of previous methods about obstacle avoidance are proposed by related work ([1-12]). Those related work has proposed the algorithm from various viewpoints. In this paper, probabilistic inference was used for path prediction of the moving obstacle. By using probabilistic inference, we thought that it could adjust to the moving obstacle which changes motion. There is [5] as study using probabilistic inference. This study method calculates position probabilities of the mobile robot using integrating the likelihoods of sensor readings over time. In contrast, the proposal algorithm is used probability density function of two-dimensional normal distribution. The proposal algorithm can calculate probability only from the position information on the moving obstacle.

There is a study about obstacle avoidance using the probabilistic inference [12]. The algorithm that this study proposes calculates the probabilistic potential field. The potential field is calculated using expected value using the position data of the moving obstacle. The existence probability of the mobile robot is repulsive potential in the probabilistic potential field. If the trajectory of the moving obstacle is variable trajectory, repulsive potential becomes low peak and wide area. The repulsive force becomes lower value. Therefore, repulsive force is low, so the risk of collision of the mobile robot. The proposal algorithm solved this problem by adjusting the repulsive force parameter.

III. Proposal Algorithm

Figure 2 shows the general flowchart of the proposal algorithm. The proposal algorithm consists of three steps. In the first step, robot system predicts the trajectory of the moving obstacle. In the second step, robot system calculates the prediction region of the moving obstacle. In the third step, robot system plans the mobile robot motion. About any of these issues are discussed in detail in this chapter.

A. Path Prediction of the Moving Obstacle

The moving obstacle is observed the position at regular time intervals. Figure 3 shows the position vector of the moving obstacle. $\mathbf{r}_i$ is the position vector of the current of the moving obstacle. $\mathbf{r}_{i-j}$ is the position vector of the past of the moving obstacle. So, $\mathbf{r}_{i-1}$ is the position vector of the moving obstacle last-minute. Now, the moving obstacle is assumed to move in the tangential direction. In other words, the moving obstacle is assumed to move in the liner direction of the vector difference $\mathbf{r}_i$ and $\mathbf{r}_{i-1}$. Therefore, position vector of the moving obstacle in the future is

$$\mathbf{r}_{i+1} = \mathbf{r}_i + \left(\mathbf{r}_i - \mathbf{r}_{i-1}\right). \quad (1)$$

$\mathbf{r}_i$-$\mathbf{r}_{i-1}$ in (1) represents tangential direction of the moving obstacle trajectory. Consequently, (1) represents that the moving obstacle moves tangential direction from the current position. The moving obstacle does not necessarily move tangential directions. So, by using the prediction region, the mobile robot adjusts the moving obstacle that did not move as prediction.

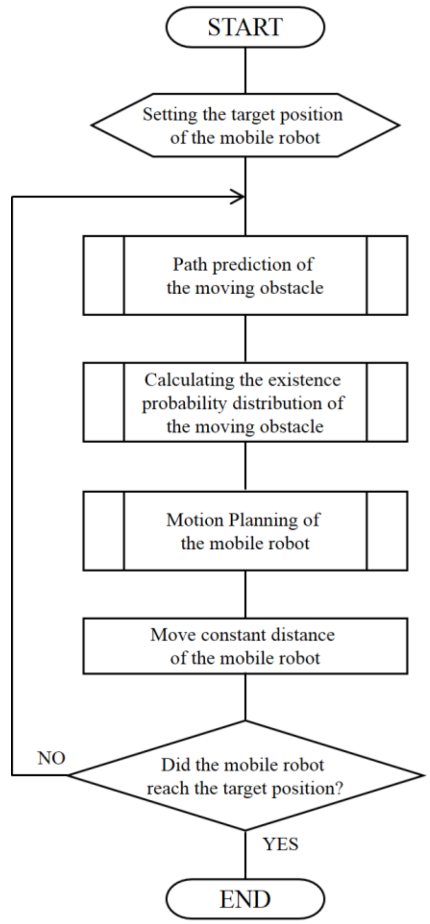


Fig. 2 General flowchart of the proposed algorithm

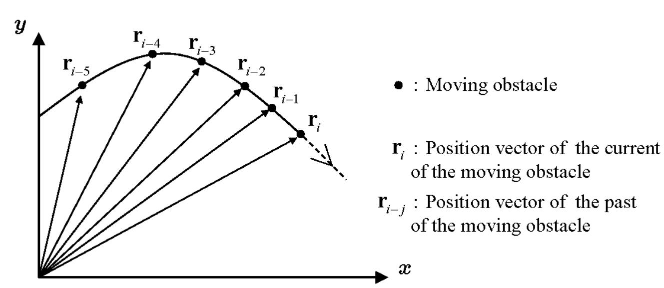


Fig. 3 Definition of the position vector of the moving obstacle

B. Prediction Region of the Moving Obstacle

The prediction region is calculated using prediction result of the moving obstacle in the preceding section. We formulated mathematical model using the probability density function of two-dimensional normal distribution. By using the probability density function of two-dimensional normal distribution, if the trajectory of the moving obstacle has much change, the prediction region can be enlarged. Equation (2) is the mathematical model to calculate the prediction region.

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{P}}\exp(-D) \tag{2}$$

Now, P and D in (2) are

$$P = 1 - \rho_{xy}{}^2, \tag{3}$$

$$D = \frac{1}{2\mathrm{P}}\left(\frac{X^2}{\sigma_x^2} + \frac{Y^2}{\sigma_y^2} - \frac{2\rho_{xy}XY}{\sigma_x\sigma_y}\right). \tag{4}$$

X and Y in (4) are

$$X = x - \mu_x, \tag{5}$$

$$Y = y - \mu_y. \tag{6}$$

μ_x and μ_y are coordinates of the prediction position of the moving obstacle. The prediction position is calculated by (1). σ_x and σ_y in (2) and (4) are variances of the moving obstacle movement. By using the variances of the moving obstacle movement, if there is much change of the motion of the moving obstacle, the variance value will become large, and if there is little change of the motion, the variance value will become small. Now, the variances of the movement of the moving obstacle are considered as shown in Fig.4. σ_x and σ_y can be written as

$$\sigma_x{}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\Delta rx_i - \Delta\bar{r}x\right)^2, \tag{7}$$

$$\sigma_y{}^2 = \frac{1}{n}\sum_{i=1}^{n}\left(\Delta ry_i - \Delta\bar{r}y\right)^2. \tag{8}$$

Δr_{xi} and Δr_{yi} are the moving obstacle movement.

$$\Delta rx_i = rx_i - rx_{i-1} \tag{9}$$

$$\Delta ry_i = ry_i - ry_{i-1} \tag{10}$$

$\Delta\bar{r}x$ and $\Delta\bar{r}y$ are the average values of the moving obstacle movement.

$$\Delta\bar{r}x = \frac{1}{n}\sum_{i=1}^{n}\left(rx_i - rx_{i-1}\right) \tag{11}$$

$$\Delta\bar{r}y = \frac{1}{n}\sum_{i=1}^{n}\left(ry_i - ry_{i-1}\right) \tag{12}$$

Now, ρ_{xy} is the correlation coefficient.

$$\rho_{xy} = \frac{\sigma_{xy}}{\sigma_x\sigma_y} \tag{13}$$

σ_{xy} is the covariance of the σ_x and σ_y.

$$\sigma_{xy} = \frac{1}{n}\sum_{i=1}^{n}\left(\Delta rx_i - \Delta\bar{r}x\right)\left(\Delta ry_i - \Delta\bar{r}y\right) \tag{14}$$

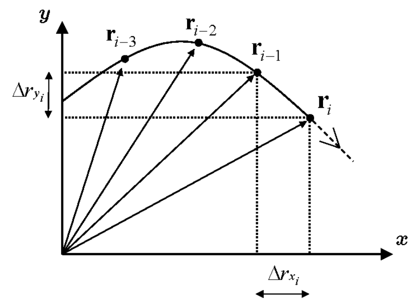


Fig. 4 Moving obstacle movement

C. Motion Planning for the Mobile Robot

The potential field method is used in the motion planning for the mobile robot. We used Khatib's potential field method [1]. The potential field method consists of the attraction potential and the repulsion potential. Now, the attraction potential $\mathbf{U}_{attract}$ and repulsion potential $\mathbf{U}_{rep}$ are

$$\mathbf{U}_{attract}(\mathbf{X}) = \frac{1}{2}C_1\left|\mathbf{X} - \mathbf{X}_{goal}\right|^2, \tag{15}$$

$$\mathbf{U}_{rep}(\mathbf{X}) = \begin{cases} \frac{1}{2}C_2\left(\frac{1}{\left|\mathbf{X} - \mathbf{X}_d\right|} - \frac{1}{p_0}\right)^2 & \left(\left|\mathbf{X} - \mathbf{X}_d\right| \le p_0\right), \\ \mathbf{0} & \left(\left|\mathbf{X} - \mathbf{X}_d\right| > p_0\right). \end{cases} \tag{16}$$

$\mathbf{X}$ is the position vector of the current position of the mobile robot. $\mathbf{X}_{goal}$ is the position vector of the target position for the mobile robot. $\mathbf{X}_d$ is the nearest position to the prediction region of the moving obstacle. C_1, C_2 and p_0 are parameters of the positive constant. By using the attraction potential $\mathbf{U}_{atrract}$ and repulsion potential $\mathbf{U}_{rep}$, the attraction force $\mathbf{F}_{attract}$ and the repulsion force $\mathbf{F}_{\mathrm{rep}}$ are calculated as

$$\begin{aligned} \mathbf{F}_{attract} &= -\nabla\mathbf{U}_{attract}(\mathbf{X}) \\ &= -C_1\left(\mathbf{X} - \mathbf{X}_{goal}\right), \end{aligned} \tag{17}$$

$$\mathbf{F}_{rep} = -\nabla\mathbf{U}_{rep}(\mathbf{X})$$

$$= \begin{cases} C_2\left(\frac{1}{\left|\mathbf{X} - \mathbf{X}_d\right|} - \frac{1}{\rho 0}\right)\frac{\mathbf{X} - \mathbf{X}_d}{\left|\mathbf{X} - \mathbf{X}_d\right|^2} & \left(\left|\mathbf{X} - \mathbf{X}_d\right| \le p_0\right), \\ \mathbf{0} & \left(\left|\mathbf{X} - \mathbf{X}_d\right| > p_0\right). \end{cases} \tag{18}$$

The virtual force $\mathbf{F}$ for the mobile robot motion is calculated by the using the attraction force $\mathbf{F}_{attract}$ and the repulsion force $\mathbf{F}_{\mathrm{rep}}$. The virtual force $\mathbf{F}$ can be written as

$$\mathbf{F} = \mathbf{F}_{attract} + \sum\mathbf{F}_{rep}. \tag{19}$$

The repulsion force $\mathbf{F}_{\mathrm{rep}}$ is totaled when the moving obstacle is plurality. The virtual force $\mathbf{F}$ is normalized, in order to remove the magnitude of the virtual force vector $\mathbf{F}$. The normalized virtual force $\mathbf{F}_0$ is

$$\mathbf{F}_0 = \frac{\mathbf{F}}{\left|\mathbf{F}\right|}. \tag{20}$$

Therefore, the next mobile robot motion $\mathbf{X}_{i+1}$ is

$$\mathbf{X}_{i+1} = \mathbf{X}_i + v\mathbf{F}_0. \tag{21}$$

v is the velocity parameter for the mobile robot.

IV. Simulation

The simulation was performed in order to investigate whether the algorithm proposed by this study is effective. All simulations were performed using Matlab.

A. Moving Obstacle Trajectory

The simulation was performed on the moving obstacle trajectory of four patterns. Figure 5 shows the case where the moving obstacle performs liner uniform motion. Figure 6 shows the case where the moving obstacle performs motion that direction is constant and velocity is random.

Figure 7 shows the case where the moving obstacle performs motion that direction is random and velocity is constant. Figure 8 shows the case where the moving obstacle performs motion that direction and velocity are random.

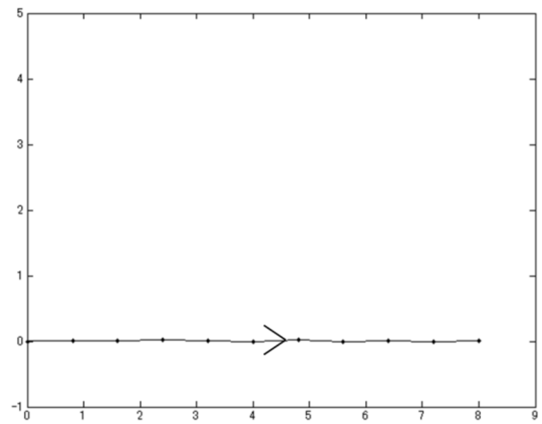


Fig. 5 Trajectory of the moving obstacle to perform liner uniform motion

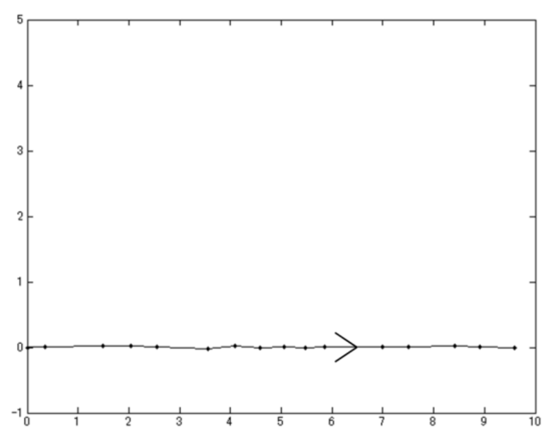


Fig. 6 Trajectory of the moving obstacle to perform motion: direction is constant and velocity is random.

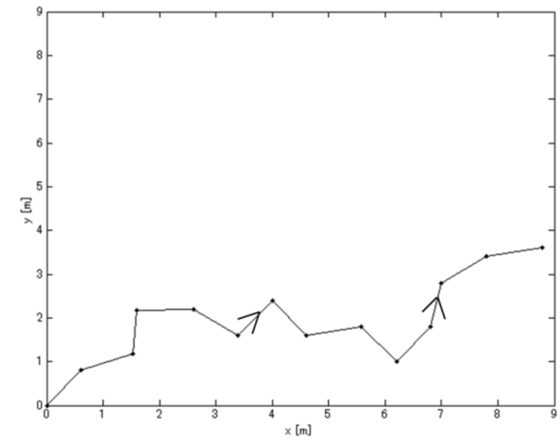


Fig. 7 Trajectory of the moving obstacle to perform motion: direction is random and velocity is constant

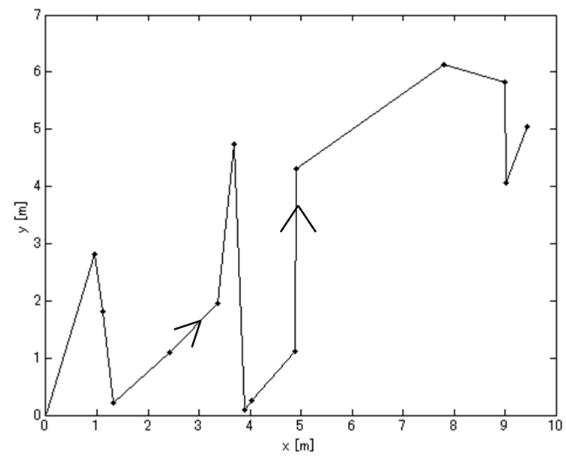


Fig. 8 Trajectory of the moving obstacle to perform motion: direction is random and velocity is random

B. Simulation Result

Table I shows simulation parameters. Figure 9 shows the simulation result of the moving obstacle trajectory in Fig.5. Figure 10 shows the simulation result of the moving obstacle trajectory in Fig.6. Figure 11 shows simulation result of the moving obstacle trajectory in Fig.7. Figure 12 shows the simulation result in Fig.8.

TABLE I
SIMULATION PARAMETERS

Parameter symbol	Value
C_1	0.010
C_2	3.5×10^{-3}
p_0	1.0
v	0.50

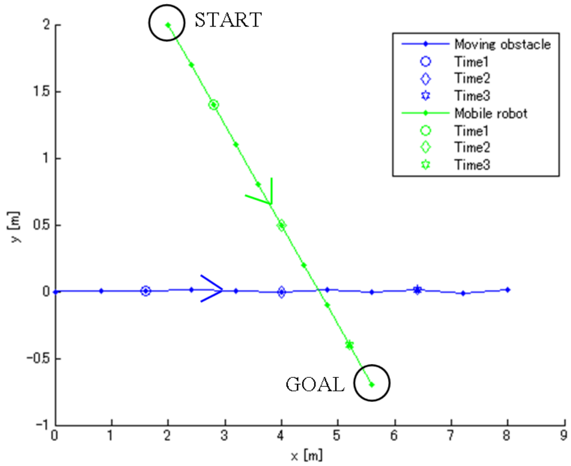


Fig. 9 Simulation result of the moving obstacle avoidance in Fig.5.

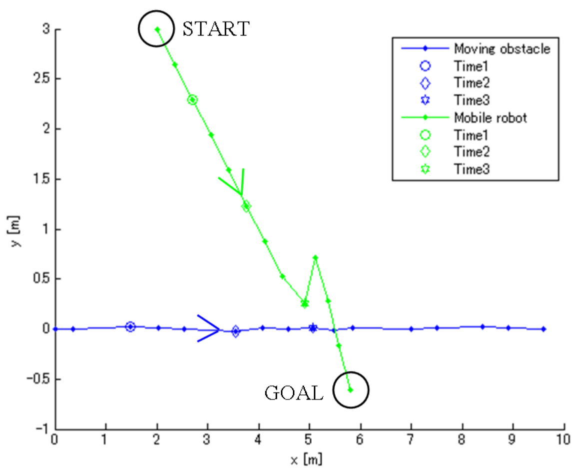


Fig. 10 Simulation result of the moving obstacle avoidance in Fig.6.

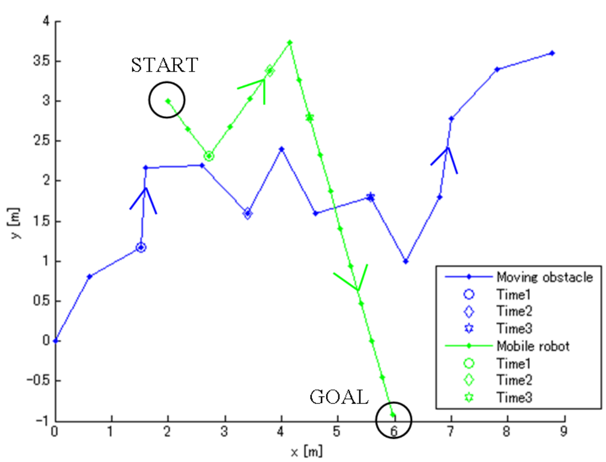


Fig. 11 Simulation result of the moving obstacle avoidance in Fig.7.

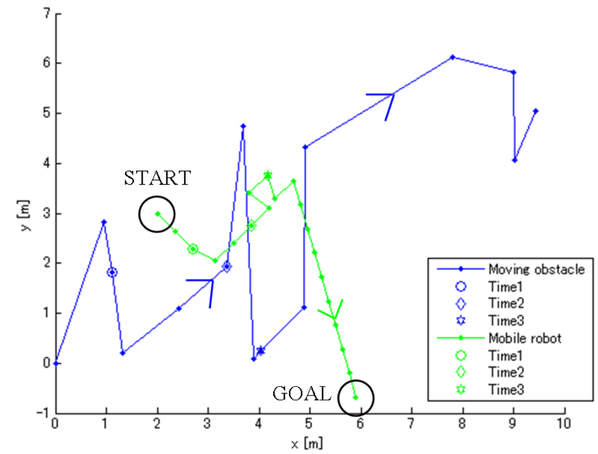


Fig. 12 Simulation result of the moving obstacle avoidance in Fig.8.

C. *Discussion*

It confirmed simulation that the mobile robot did not collide with the moving obstacle by using the proposal algorithm. But the mobile robot did not perform avoidance motion for the moving obstacle in Fig.9. A cause is because the prediction region for the moving obstacle is very small. Figure 13 shows the prediction region that the mobile robot approaches the moving obstacle most in Fig.9. It can be said that the prediction region in Fig.13 as compared with Fig.14. Since the prediction region was very small, the mobile robot did not avoid the moving obstacle. When the moving obstacle performs a constant motion, the prediction region becomes very small. Therefore, the proposal algorithm requires a certain improvement.

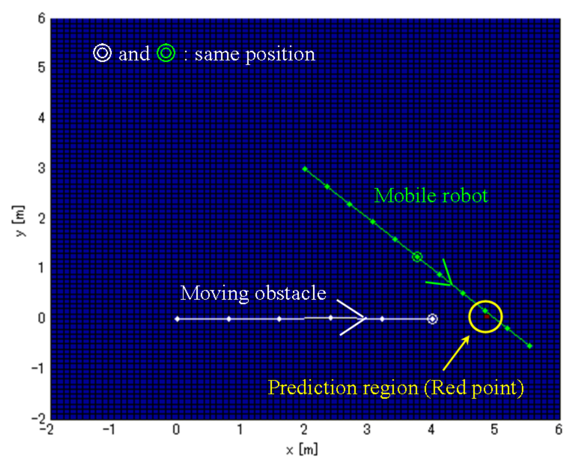


Fig. 13 Prediction region that the mobile robot approaches the moving obstacle most in Fig.9.

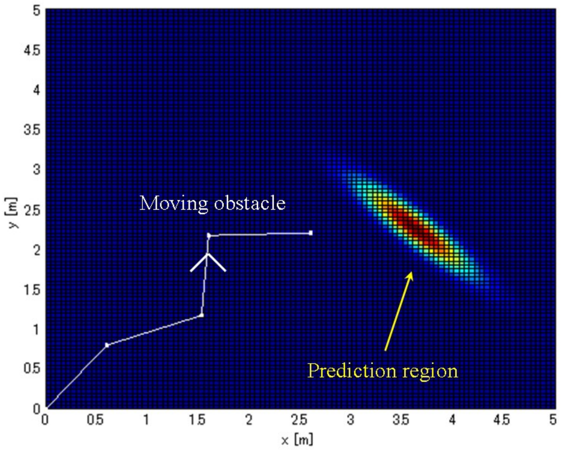


Fig. 14 Prediction region in Fig.11.

V. CONCLUSION

This paper presented the motion planning algorithm of the moving obstacle avoidance for the mobile robot using the probabilistic inference. In this method, the prediction region is calculated by using the mathematical model based on the probability density function of two-dimensional normal distribution. By simulations, we tested whether the mobile robot can avoid the moving obstacle and reach the target position. The mobile robot can avoid the moving obstacle was confirmed by simulation results.

However, current results are met optimal answer against the given environment and situation. We have to verify whether the proposal algorithm is applicable even when the moving obstacle is plurality. The proposal algorithm is improved based on the verified result.

The proposal algorithm does not consider sizes of the moving obstacle and the mobile robot. This problem is solved by introducing sizes of the moving obstacle and the mobile robot into the proposal algorithm. The experiments are very different from the simulations. Therefore, we experiment by an actual robot.

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