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Moving Obstacle Avoidance Control by Fuzzy Potential Method and Model Predictive Control

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Abstract— **In this paper, we propose an obstacle avoidance method considering both the shape and dynamics of robot and the motion of obstacles, using model predictive control (MPC) and fuzzy potential method (FPM). FPM can deal with the shape of robot, but it cannot treat the dynamics of robot. On the other hand, MPC can deal with constraints including the dynamics of both robot and obstacles. The predicted movable range of obstacles is used as a prohibited region for MPC. Thus, combining FPM and MPC, the proposed method achieves moving obstacle avoidance. The effectiveness of the proposed method is verified through numerical simulations.**

I. INTRODUCTION

In recent years, usage of mobile robot has been increased especially in automation of factories. Omni-directional robot can move in arbitrary direction and attitude and is useful in a narrow environment. When the robot is used in such environments, obstacle avoidance is an important task. Thus various obstacle avoidance methods for mobile robot have been researched [1]–[5]. Especially if the robot is rectangular, avoidance control considering its shape and attitude is required. As such a control method, *fuzzy potential method* (FPM) was proposed [6]. FPM achieves obstacle avoidance considering the shape of robot using translational and rotational motion. These motions are generated by fuzzy calculation based on the priority about a goal and obstacles. In addition, FPM does not require informations of obstacles in advance and can avoid reactively. Since the dynamics of robot is not considered, however, a steep change of control input may occur and cause failure of actuator. One way to consider the dynamics is *model predictive control* (MPC) [7]. MPC is one of the optimal control method which can explicitly deal with various constraints including the dynamics. Also *fuzzy potential model predictive control* (FPMPC) which is comprised of MPC and FPM was proposed [8]. In this method, the framework of FPM is incorporated into an index function of MPC while treating the dynamics as the constraint. FPMPC realizes avoidance considering both the shape and dynamics. However, these methods assume that obstacles are static.

Thinking about the environment of factory, an avoidance method which can be adapted to moving obstacles is needed. To conduct this problem, the method using velocities of the robot and obstacles was proposed [9]. This method obtains the reachable range from the speed and acceleration of robot and the range including possibility of collision from the relative speed and then combines these ranges. As an alternative one, the method which extends FPM was proposed [10]. This method adapts to moving obstacles by calculating FPM based on relative velocities. In addition, the potential field method consisting of relative velocities between the robot and obstacles was proposed [11]. This method is comprised of two potential fields. One is generated by a relative position. The other is calculated by a relative velocity. On the other hand, the method locally modifying a global reference path when obstacles are detected was proposed [12]. In this method, obstacle avoidance is realized by assuming a repulsing force from obstacles and putting it into the index function of MPC. Furthermore, the method with potential field based on modeling of obstacles was proposed [13]. In this method, the predictive moving direction of an obstacle is expressed as a potential field of von Mises distribution. Unfortunately in these methods, the shape of the robot was not explicitly considered. Thus an avoidance method which can be adapted to moving obstacles and consider both the shape and dynamics is needed.

In this paper, we propose an obstacle avoidance method considering the moving obstacles by extending FPMPC. In the method, the robot predicts the motion of obstacles in the predictive horizon of MPC by assuming that the speed of them is known. By giving the obtained moving range of obstacles as a prohibited region against the robot, the method guarantees moving obstacle avoidance. Moreover the method considers both the shape and dynamics of robot based on FPMPC. The performance is verified by numerical simulations where the proposed method realizes moving obstacle avoidance with adequate control of the moving direction and the attitude by predicting the motion of obstacles. Moreover, we show that the method can be used in various environments by simulating in a complex situation.

II. CONTROLLED OBJECT

The model of robot is depicted in Fig. 1. The center of gravity and attitude angle are denoted as $(X_\mathrm{g}, Y_\mathrm{g}, \theta_\mathrm{r})$ on the inertial coordinate. The input velocity for each direction is denoted as $(u_x, u_y, \omega_\mathrm{r})$ on the coordinate $x-y$ fixed to the robot. The kinematic equation of robot is represented by

$$\dot{X}_\mathrm{g} = v_\mathrm{c}\cos(\theta_\mathrm{t} + \theta_\mathrm{r}), \tag{1}$$

$$\dot{Y}_\mathrm{g} = v_\mathrm{c}\sin(\theta_\mathrm{t} + \theta_\mathrm{r}), \tag{2}$$

$$\dot{\theta}_\mathrm{r} = \omega_\mathrm{r}, \tag{3}$$

$$\dot{\theta}_\mathrm{t} = \omega_\mathrm{t}, \tag{4}$$

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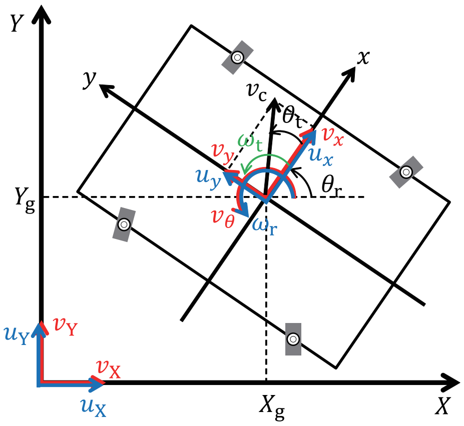
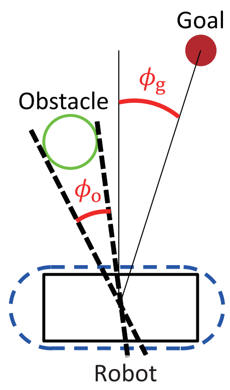
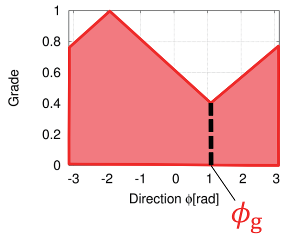


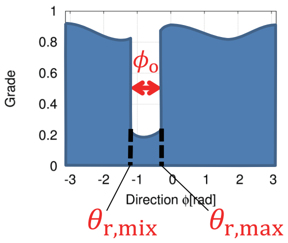
Fig. 1. Model of robot.



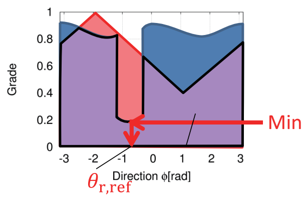
(a) Rotation situation.



(b) PMF of a goal.



(c) PMF of a obstacle.



(d) Integrated PMF.

Fig. 2. Design of PMF for rotational motion.

where θ_t, ω_t and v_c are the translational moving direction, its time derivative and the speed of the robot, respectively. ω_t and ω_r controls the translational movement direction and the attitude angle, respectively. In this study, the state vector is $\boldsymbol{x} = [X_g, Y_g, \theta_r, \theta_t]$ and the input vector is $\boldsymbol{u} = [\omega_r, \omega_t]$.

III. FUZZY POTENTIAL MODEL PREDICTIVE CONTROL [8]

A. Fuzzy Potential Method [6]

Fuzzy potential method is a kind of the obstacle avoidance method considering the shape of robot and combining rotation and translation. To consider the shape, we design a capsule case which covers the robot. In addition, we design *potential membership function* (PMF) based on the robot shape, positions of obstacles and a goal direction. Summaries of PMF in rotation and translation are depicted in Fig. 2 and 3, respectively. In the rotational motion, PMFs concerning the goal direction ϕ_g and obstacles are designed as depicted in Fig. 2(b) and 2(c), respectively. Integrating these PMFs as depicted in Fig. 2(d), the direction which has the minimum grade is treated as the reference rotational direction. On the other hand, in the translational motion, PMFs concerning the goal direction ϕ_g and obstacles are designed as depicted in Fig. 3(b) and 3(c), respectively. Integrating these PMFs as depicted in Fig. 3(d), the direction which has the maximum grade is treated as the reference translational direction. Each PMFs in both motions generate the reference angles which turn the robot to face the obstacles and guide the robot to the goal in the range ensuring avoidance. Thus, FPM realizes obstacle avoidance while using translational and rotational motion.

B. Model Predictive Control

Model predictive control is an optimal control method which obtains the optimal control input by minimizing the index function with prediction of the future motion of robot. The index function is given by

$$J(\boldsymbol{x}(\tau), \boldsymbol{u}(\tau)) = \phi(\boldsymbol{x}(t+T)) + \int_t^{t+T} L(\boldsymbol{x}(\tau), \boldsymbol{u}(\tau))\mathrm{d}\tau, \tag{5}$$

where $t, T, \phi(\cdot)$ and $L(\cdot)$ are current time, predictive length, terminal cost and stage cost, respectively. The optimal control input $\boldsymbol{u}^*(\tau)(t \le \tau \le t+T)$ is generated by solving the following optimization problem:

$$\boldsymbol{u}^*(\tau) = \arg\min_{\boldsymbol{u}} J(\boldsymbol{x}, \boldsymbol{u}), \tag{6}$$
$$\text{subject to } \dot{\boldsymbol{x}}(t) = f(\boldsymbol{x}(t), \boldsymbol{u}(t)).$$

$\boldsymbol{u}^*(t)$ is used as an actual control input.

C. Algorithm of FPMPC

In FPMPC, we apply MPC to both the rotational and translational motion of FPM.

The index function J_r about the rotation is represented by

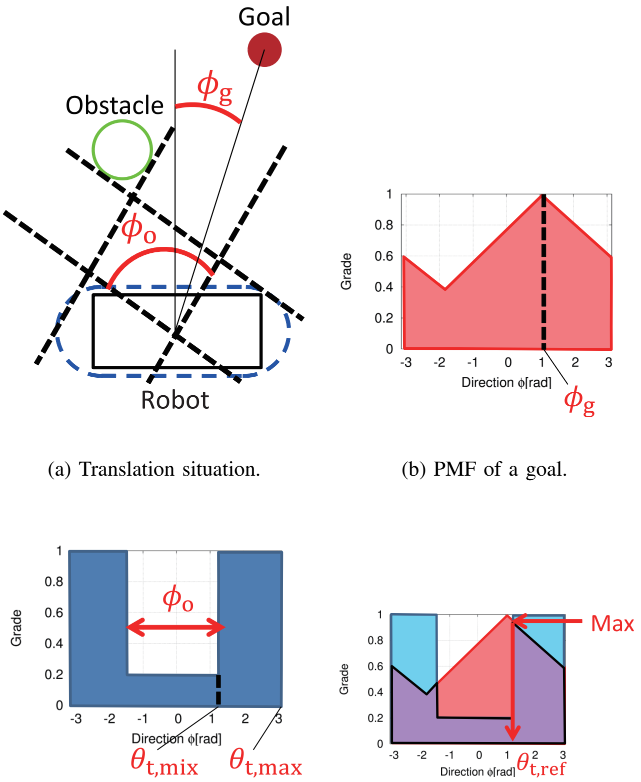
$$J_r = \phi_r(\theta_r(t+T)) + \int_t^{t+T} L_r(\theta_r(\tau), \omega_r(\tau))\mathrm{d}\tau + \int_t^{t+T-1} l_r(\omega_r(\tau))d\tau, \tag{7}$$

$$\phi_r(\theta_r(t)) = S_r|\theta_r(t) - \theta_{r,ref}(t)|, \tag{8}$$

$$L_r(\theta_r(t), \omega_r(t)) = Q_r|\theta_r(t) - \theta_{r,ref}(t)| + R_r\omega_r(t)^2, \tag{9}$$

$$l_r(\omega_r(t)) = P_r(\omega_r(t+1) - \omega_r(t))^2, \tag{10}$$

where S_r, Q_r, R_r and P_r are weights. We evaluate the error between the reference and attitude angle, the magnitude of the control input and its derivative. In order to integrate



(a) Translation situation. (b) PMF of a goal.

(c) PMF of a obstacle. (d) Integrated PMF.

Fig. 3. Design of PMF for translational motion.

FPM with MPC, we formulate the index function by approximating PMF with convex function. The constraints are represented by

$$\dot{\theta}_{\mathrm{r}} = \omega_{\mathrm{r}}, \tag{11}$$

$$\theta_{\mathrm{r,min}} \leq \theta_{\mathrm{r}} \leq \theta_{\mathrm{r,max}}. \tag{12}$$

Assuming that the control cycle is short, the predicted positions are computed by current state $\boldsymbol{x}$ and the control inputs $\omega_{\mathrm{r}}^{*}(\tau)$ and $\omega_{\mathrm{t}}^{*}(\tau), (t \leq \tau \leq t+T)$ which are generated in prior sampling. The reference angle $\theta_{\mathrm{r,ref}}$ is computed by rotational PMFs based on these predicted positions. In addition, both $\theta_{\mathrm{r,max}}$ and $\theta_{\mathrm{r,min}}$ in (12) are determined by the location of obstacles. Thus the rotational angle and input which consider the dynamics and turn the front of robot to a neighboring obstacle are obtained.

The index function J_{t} about the translation is represented by

$$J_{\mathrm{t}} = \phi_{\mathrm{t}}(\theta_{\mathrm{t}}(t+T)) + \int_{t}^{t+T} L_{\mathrm{t}}(\theta_{\mathrm{t}}(\tau), \omega_{\mathrm{t}}(\tau)) \mathrm{d}\tau + \int_{t}^{t+T-1} l_{\mathrm{t}}(\omega_{\mathrm{t}}(\tau)) d\tau, \tag{13}$$

$$\phi_{\mathrm{t}}(\theta_{\mathrm{t}}(t)) = S_{\mathrm{t}}|\theta_{\mathrm{t}}(t) - \theta_{\mathrm{g}}(t)|, \tag{14}$$

$$L_{\mathrm{t}}(\theta_{\mathrm{t}}(t), \omega_{\mathrm{t}}(t)) = Q_{\mathrm{t}}|\theta_{\mathrm{t}}(t) - \theta_{\mathrm{g}}(t)| + R_{\mathrm{t}}\omega_{\mathrm{t}}(t)^{2}, \tag{15}$$

$$l_{\mathrm{t}}(\omega_{\mathrm{t}}(t)) = P_{\mathrm{t}}(\omega_{\mathrm{t}}(t+1) - \omega_{\mathrm{t}}(t))^{2}, \tag{16}$$

where $S_{\mathrm{t}}, Q_{\mathrm{t}}, R_{\mathrm{t}}$ and P_{t} are weights. We evaluate the error between the reference and current angles, the magnitude of the control input and the differences of input between control cycles. To integrate PMF with MPC, we formulate the index function by convex function using absolute vale. The constraints are represented by

$$\dot{\theta}_{\mathrm{t}} = \omega_{\mathrm{t}}, \tag{17}$$

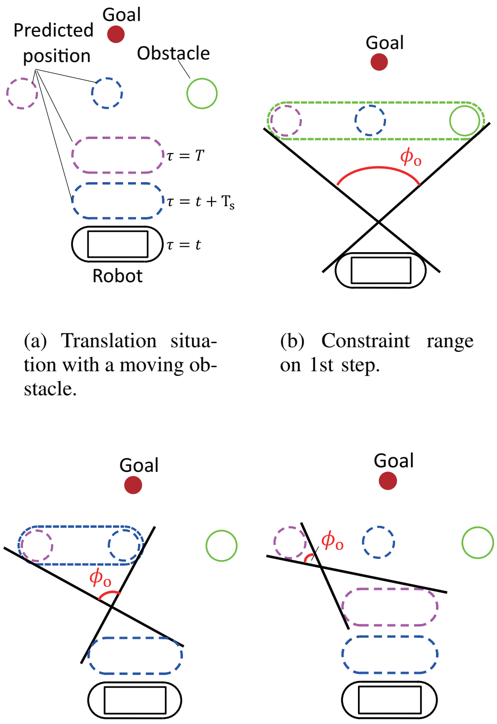
$$\theta_{\mathrm{t,min}} \leq \theta_{\mathrm{t}} \leq \theta_{\mathrm{t,max}}. \tag{18}$$

The predicted positions in translation are computed by updating only the orientation $\boldsymbol{x}(\tau), (t \leq \tau \leq t+T)$ using optimal inputs $\omega_{\mathrm{r}}^{*}(\tau), (t \leq \tau \leq t+T)$. The goal angle θ_{g} is computed by translational PMFs based on these predicted positions. In addition, both $\theta_{\mathrm{t,max}}$ and $\theta_{\mathrm{t,min}}$ in (18) are determined based on existence range of obstacles. If plural ranges are generated, the nearest range to a goal is used for constraints. Thus obstacle avoidance is guaranteed by the constraints. The translational movement direction and input are obtained by optimizartion considering the dynamics.

IV. PROPOSED METHOD

In FPMPC, it is assumed that obstacles are stationary. It is desirable that avoidance methods can be used in time-varying environments because of practical use. In this study, we propose an obstacle avoidance method which can be adapted to the motion of obstacles by extending the constraint concerning the translation in FPMPC. In conventional FPMPC, the constraint about the translational motion in (18) is obtained by designing PMF on each predictive position as depicted in Fig. 3. Since the motion of obstacles are not considered in the predicted positions, the constraints on each predictive position may becomes inappropriate and then collision with moving obstacles may happen. Thus the proposed method determines new constraints for each predictive position considering the motion of obstacles.

A summary of the proposed method is depicted in Fig. 4 and the algorithm is described as follows, where $\mathrm{T_s}$ is a predictive step width. First, assuming the speed of obstacles is fixed, the position of obstacle corresponding to each predictive step of MPC is obtained as depicted in Fig. 4(a). Dashed lines of same color indicate the robot and obstacle in the same step. Next, when computing the constraints on each predictive step, we design the capsule which includes the terminal step as depicted in Fig. 4(b). PMF is designed with this capsule as depicted in Fig. 3(c), where the capsule covers the range where obstacles move from each step to the terminal of horizon. The prohibited range considering the motion of obstacle is obtained and sets as the constraint. This range shrinks as the predictive step proceeds as depicted in Fig. 4(c) and 4(d). Although the constraint is given as overhanging the front of obstacle, this indicates the front of moving obstacle is dangerous. Also the prohibited range stretches when obstacles move fast, this suggests that fast obstacles are dangerous. PMF concerning a goal is designed as depicted in Fig. 3(b). In addition, integrating the PMF concerning obstacles and a goal as depicted in Fig. 3(d),



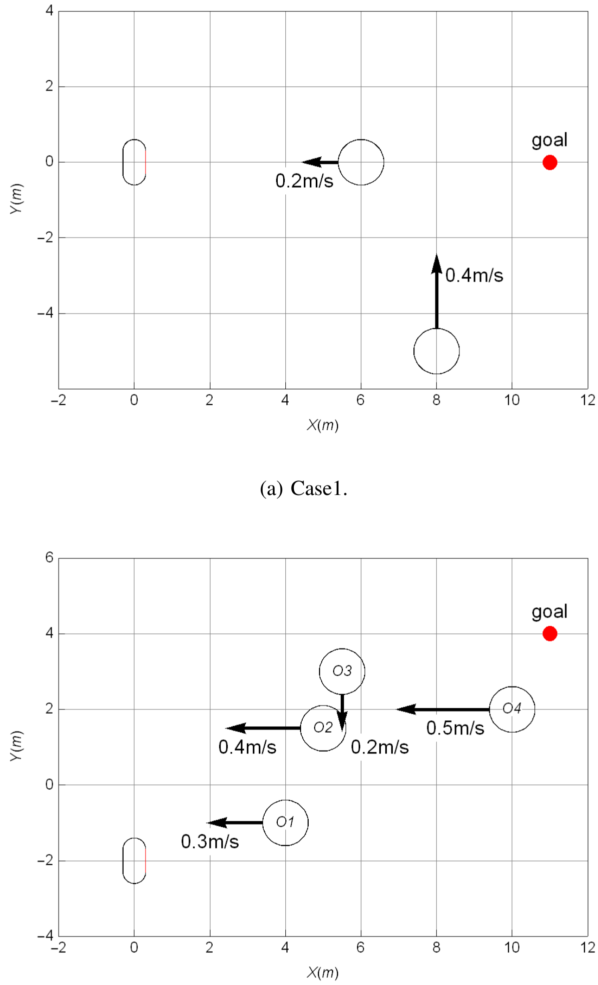
(a) Translation situation with a moving obstacle.

(b) Constraint range on 1st step.

(c) Constraint range on 2nd step.

(d) Constraint range on 3rd step.

Fig. 4. Design of constraint for translational motion in dynamic environment.



(a) Case1.

(b) Case2.

Fig. 5. Simulation situations.

the reference translational direction is obtained. The moving obstacle avoidance is guaranteed by considering the motion of them till the terminal of horizon. Thus the proposed method achieves obstacle avoidance considering the shape and dynamics of robot and the motion of obstacles.

V. SIMULATION

A. Simulation condition

We perform numerical simulations using 1.0×0.4 m robot. We conduct simulations in 2 cases. In Case 1, we show the advantage of the proposed method by comparing with FPMPC as a conventional method. In Case 2, we also show the effectiveness by the simulation in a complex situation. The initial position of robot, the goal position, the position of obstacles and velocity of them are summarized in Fig. 5 for each case. Each parameter is summarized in Table I.

B. Simulation result

The simulation result of the proposed method in Case 1 is depicted in Fig. 6 and the result of the conventional method is depicted in Fig. 7. In the proposed method, the robot avoids obstacles and reaches the goal. In the conventional method, the optimization fails at 13 s and the simulation stops. Both figures depict the motion of robot every 2 s, and painted circles and a blue line are the obstacles and the trajectory, respectively. The robot and obstacles as same color depict each position at the same time. In the proposed method, the robot moves to y axis positive direction faster than the conventional when it avoids first obstacle because the prohibit range overhangs the front of obstacle. In addition, after passing first one, the robot goes to the front of second one and then changes the translational direction to the backside of it at $X = 6$ m. The prohibited range generated in front of the obstacle is so large that the robot decides to change the moving direction. On the other hand, in the conventional method, the optimization fails before avoiding the second obstacle. Because the motion of obstacle is not considered in the prediction, the constraint cannot be satisfied in the next control step and the optimization fails. Thus we consider the proposed method has advantage on avoidance of moving obstacles.

The simulation results of the proposed method in Case 2 are depicted in Fig. 8 and 9. Figure 8 depicts the control inputs. Figure 9 depicts snapshots in 5, 8, 12 and 15 s after starting the simulation. The capsule case, circles and blue line are the robot, obstacles and trajectory, respectively.

TABLE I

PARAMETER SETTING.

Predictive length	3.5 s
Number of predictive steps	10
Vehicle velocity v_{c}	0.5 m/s
Weight S_{r}	1.0
Weight Q_{r}	100
Weight R_{r}	0.01
Weight P_{r}	1
Weight S_{t}	0.01
Weight Q_{t}	100
Weight R_{t}	0.01
Weight P_{t}	10

Firstly, the robot moves to the direction detouring O_1 and O_2, and then changes the direction because it judges that it can pass through a gap between obstacles by changing its attitude at $t = 5$ s. After that the robot achieves avoidance by controlling its attitude adequately at $t = 8$ s. Secondly, after passing O_1 and O_2, the robot goes to the front of O_3 because the positions of O_3 and O_4 prevent the robot moving to the goal. Since the gap between O_3 and O_4 becomes wide at $t = 12$ s, the robot changes the direction because it judges that it can move to the backside of O_3. Finally, the robot changes its attitude adequately and avoids O_3 at $t = 15$ s and then it reaches the goal. On the other hand, the optimization in the conventional method fails after passing O_1 and O_2, where the result of simulation is omitted due to the limitation of pages. In addition, the maximum value of ω_r in the conventional method is four times larger than the proposed one. In the proposed method, the excessive control input is suppressed as depicted in Fig. 8 due to the consideration of the motion of obstacles. The proposed method adequately controls the attitude and translational direction of robot adjusted to the motion of obstacles in the environment with moving obstacles. Thus it is shown that the proposed method can adapt to a complex environment.

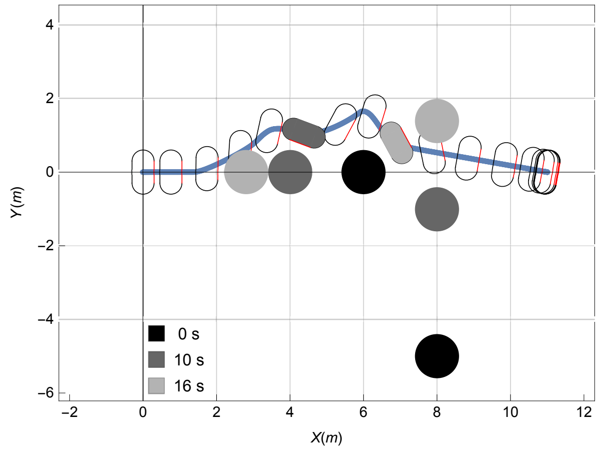


Fig. 6. Simulation result of the proposed method in Case 1.

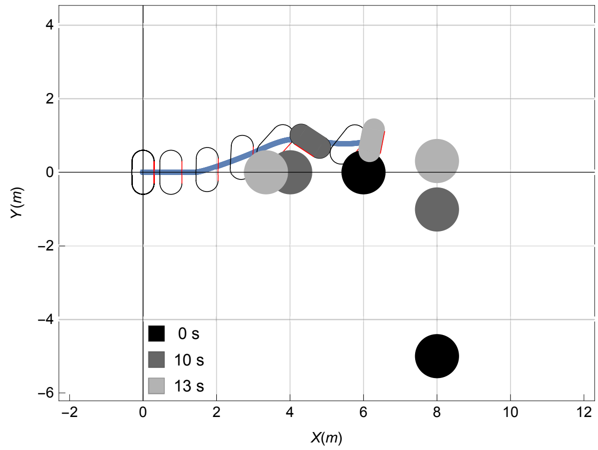


Fig. 7. Simulation result of the conventional method in Case 1.

VI. CONCLUSIONS

In this paper, we proposed an obstacle avoidance method adapted to moving obstacles. The proposed method is composed of fuzzy potential method and model predictive control. Although fuzzy potential method can deal with the shape and attitude of robot and achieves obstacle avoidance by translational and rotational motion, the dynamics of robot and the motion of obstacles cannot be explicitly included. Model predictive control realizes optimal control based on an index function while predicting the motion of robot and considering the dynamics of robot by handling the constraint explicitly. In addition, by considering the mobility range of obstacles as constraints, it guarantees obstacle avoidance. Thus we realize obstacle avoidance considering the shape, attitude and dynamics of robot and the motion of obstacles. In this paper, we verified the performance of the proposed method in numerical simulations. The proposed method achieves obstacle avoidance in the situation where the conventional method fails. Also in complex situation, the proposed method achieves obstacle avoidance adapting to the motion of obstacles. Therefore we show the proposed method is efficient in several situation. In the future work, we will verify the performance in experiments.

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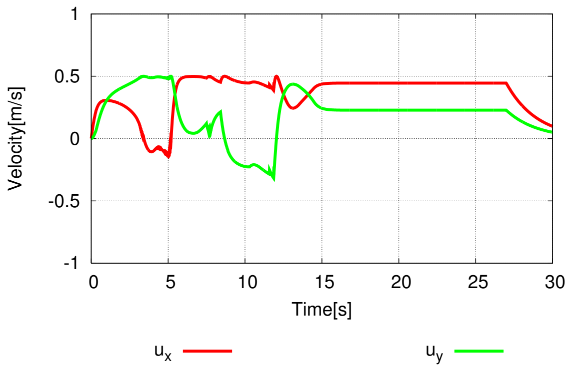
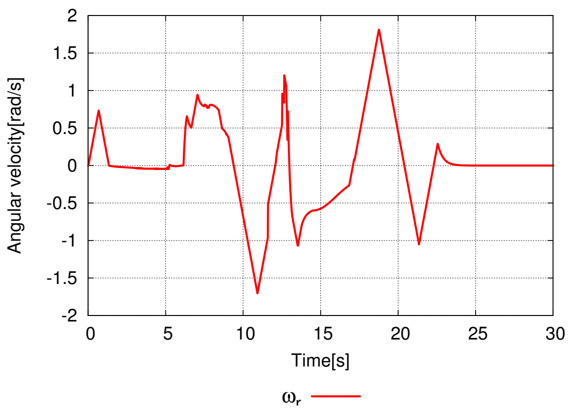
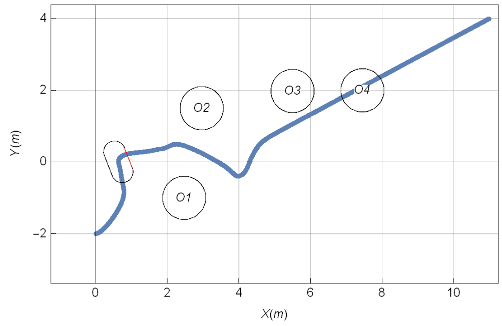


(a) Control inputs u_x, u_y.

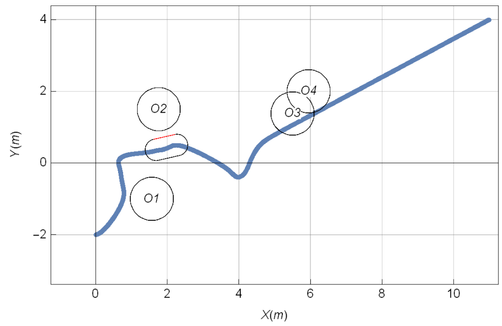


(b) Control input ω_r.

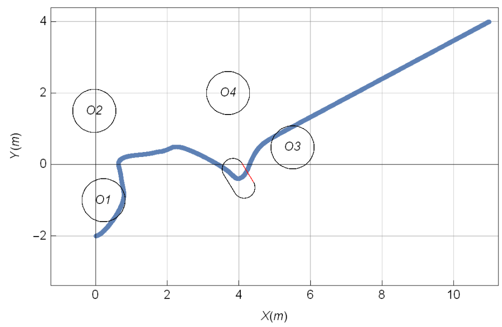
Fig. 8. Control inputs of the proposed method in Case 2.



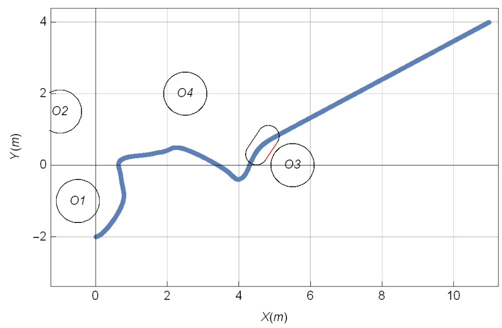
(a) $t = 5$ s.



(b) $t = 8$ s.



(c) $t = 12$ s.



(d) $t = 15$ s.

Fig. 9. Simulation result of the proposed method in Case 2.

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