Soft Target Based Obstacle Avoidance for Car-like Mobile Robot in Dynamic Environment

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***Abstract*— The real time flexible operation of a car-like mobile robot with nonholonomic constraints in dynamic environment is still a very challenging problem. The difficulty lies in the setting of moving sub-target in real-time and appropriately to obtain a collision-free and low cost path. In this paper, we present a new approach to obstacle avoidance for mobile robots in a narrow area with static and dynamic obstacles. It is based on selection of the sub-target points of robot's movement called "soft target" which is a target set defined as all possible and reachable via-points in a navigation space. The soft target is acquired by on-line learning based on the final target and environment information. Each element of it has its membership value between 0 to 1 denoting its evaluation. The algorithm of the presented method is realized by fuzzy predictive control (FPC). The simulation results show the validity and effectiveness of the proposed robot motion control method.**

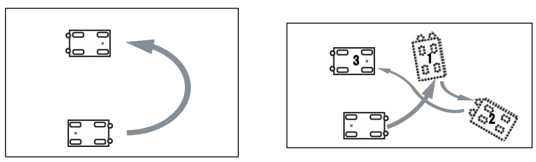
I. Introduction

The motion control problem for mobile robots can be typically formulated as planning a path between two specified locations, which is collision-free and satisfies certain optimization criteria.

It have been extensively researched and many methods for obstacle avoidance have been proposed, such as potential force field method[1], behavior-based navigation[2], fuzzy decision making theory[3], and so on, and significant results have been obtained in the past decades[4,5,6]. However, many of the existing methods are inflexibility in responding to changes in the environment and poor to respond to uncertainties, or rely on some knowledge of the global environment. Most of them suppose that the map is wide enough and the robot can reach its target without any three-point turns but just by U-Turns (Figure 1) which require wide streets or cars that can turn in a very small area, or the control target is just the location ex the orientation. In fact, in a narrow area, it is possible that the robot can not reach the target if without three-point turns because of the constraint of minimal turning radius or the disturbances of obstacles. The car parking problem in a static environment has been studied by Prof. Yasunobu. A fuzzy target based controller have been proposed[7], and it solved the parking problem in a fixed space without moving obstacles. But because the target is acquired off-line for a parking lot, when the final target or map changed, target had to been explored once more. It is difficult to respond to the dynamic environment such as moving obstacle, arbitrary placement of obstacles or discretional initial position of the car.

Human's action decision (Figure 2) is based on wide targets and can respond flexibly under different situations just based on information which are intrinsically vague, imprecise and fuzzy[8]. They control a system according to its internal characteristics and the external environment synchronously, their decisions are based on a series of candidate targets and the best alternative is selected in real-time based on experiences by predicting and evaluating the state of the object with taking dynamic restrictions into account. The wide targets can be regarded as a "soft target" set and the best alternative is adjusted dynamically with the changing of environment.

Is it possible for an autonomous moving body to act based on wide targets like human in a dynamic environment and to realize a flexible operation? The answer is affirmative. So, the problem that mobile robot responds to a dynamic environment flexibly like human is considered in this paper. We proposed a soft target based intelligent PFC controller to realize a flexible autonomous operation for a car-like mobile robot with nonholonimic constraints in a dynamic environment.



(a) U-turns (b) Three-point turns

Fig. 1. Image of U-turns and three-point turns

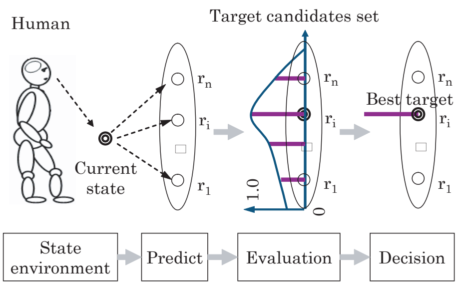


Fig. 2. Decision process of human

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II. Soft target control method

A. Soft Target

In this paper, soft target is defined as a target set and is converted into target setting knowledge by soft computing. It is constructed by fuzzy logic based on the final target and constraint information, and can be expressed as a control target set defined by fuzzy set, which includes many alternative candidates. Each candidate has its membership value defined as satisfaction grade in the range from zero to one [9].

It is denoted as Figure 3(a), and can be expressed by the membership function of enumeration type.

The total set of the target is assumed as R. Soft target $\widetilde{T_n}$ assumed to be a control target can be defined by the following expression in state c_n of the object.

$$\widetilde{T_n} = \int_R \mu_{\widetilde{T_n}}(r_i)/r_i, \qquad r_i \in R. \tag{1}$$

Here, $\widetilde{T_n}$ is the soft target set and $\mu_{\widetilde{T_n}}(r_i)$ is the membership value of alternative r_i corresponding with the state c_n.

As shown in Figure 3(b), target setting knowledge can be expressed as set clusters which correspond with different state. According to different current state c_n(a ~ f), the soft target candidate set is $\widetilde{T_n}$(a ~ f) respectively. Once the target is set, it is possible for the system to select the best alternative candidate instruction corresponding with one of the substitutable target element r_i by predictive fuzzy control method [10].

By using soft target, it is possible to construct an intelligent controller for a system with dynamic or uncertain environment to realize the real time flexible operation of an autonomous mobile body.

B. Intelligent control system design based on soft target

The configuration of system based on soft target can be outlined as shown in Figure 4. It is composed of three parts: state detecting part, soft target setting part and decision making part.

1) Detector Part: This part is detecting the state variables and the obstacles information, judging the attainment degree to the final target and the contact degree to the obstacles. When the constraints make it difficult to reach the final target directly, the target setting instruction is outputted to the soft target setting part.

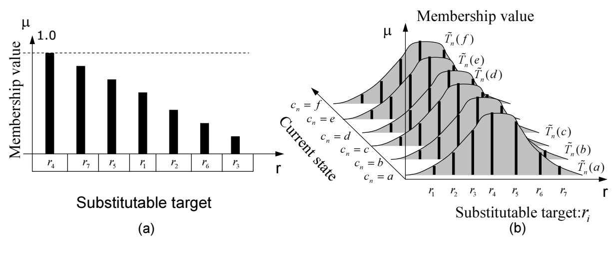


Fig. 3. Definition of soft target

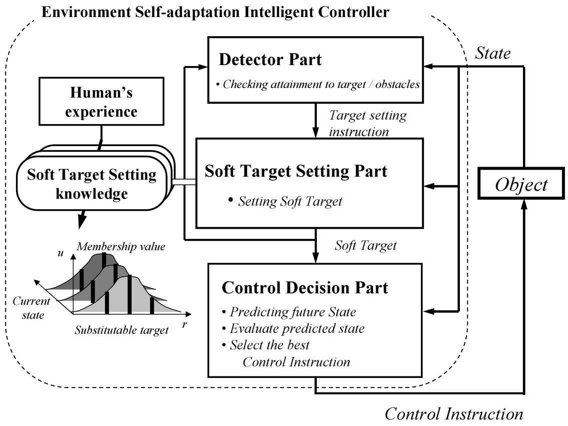


Fig. 4. Outline of the proposed system based on soft target

2) Soft Target Setting Part: When target setting instruction is received, the soft target setting part sets new target based on the soft target set according to the current state from the acquired target setting knowledge based on the final target and constraint information in advance.

3) Control Decision Part: In this part, the control decision is made as following process. Firstly, each element of soft target is assumed as the control target, and the operation instruction candidate to each target is calculated. Next, the future state of controlled object is predicted by using all the operation instruction candidates in parallel. Then the future state is evaluated by fuzzy inference, and the evaluation value of the operation instruction candidate is calculated. Lastly, the operation instruction candidate with the highest evaluation value is selected and given to the object as a control instruction.

These operations are repeated in the whole control process. Thus, the intelligent control system based on soft target is realized.

III. Application to car-like robot in dynamic environment

A. Characteristics of Four-wheeled Mobile Robot

In this research, the robot is defined as a four-wheeled vehicle with Ackerman Steering (Figure 5). The configuration of it can be denoted by $q = [x, y, \theta, \phi]^T \in \mathbb{R}^4$. Where, (x, y) is the Cartesian location of the center of its rear wheels, θ is the heading angle between the body axis and the horizontal axis, ϕ_L and ϕ_R are relative steering angle of left and right wheel respectively, and $\phi = (\phi_L + \phi_R)/2$ represents the steering angle with respect to the car body ($|\phi| \leq \phi_{\max}$). L is the wheelbase (longitudinal wheel separation). b is the width of car (lateral wheel separation). R is turning radius which is the distance between instantaneous center of curvature (ICC) to centerline of the vehicle. This system has 2 degrees of nonholonomy since the constraints on the system arise by allowing the wheels to roll and spin, but not slip. Thus, the Pfaffian constraints on the mobile robot become:

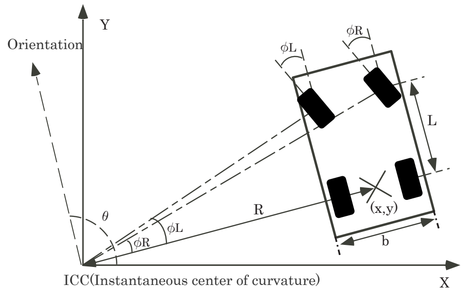


Fig. 5. Model of Ackerman steering mobile robot

$$\sin(\theta+\phi)\dot{x} - \cos(\theta+\phi)\dot{y} - L\cos\phi\cdot\dot{\theta} = 0$$
$$\sin\theta\cdot\dot{x} - \cos\theta\cdot\dot{y} = 0 \qquad (2)$$

Choosing $u_1 = v\cos\phi$ and $u_2 = \dot{\phi}$ as inputs yields:

$$\dot{q} = \begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \\ \dot{\phi} \end{pmatrix} = \begin{pmatrix} \cos\theta \\ \sin\theta \\ \frac{\tan\phi}{L} \\ 0 \end{pmatrix} u_1 + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} u_2 \qquad (3)$$

Where, v is the driving speed, u_1 corresponds to the translational velocity of the rear wheels and u_2 corresponds to the angular velocity of the steering wheels. Obviously, (3) is a so-called driftless nonlinear system with 2 inputs (v, ϕ) and 3 outputs (x, y, θ) constrained by $R_{\min} = L/\tan\phi_{\max}$. Where, R_{min} is the minimal turn radius, ϕ_{max} is the maximal steering angle.

B. Problem Description

We considered a mobile robot about the same size as a actual car moving in a $30m \times 15m$ map with static and dynamic obstacles as denoted in Figure 6. The final target is able to be set as we want. The static obstacles can be placed at any position with arbitrary shape, and the robot can start at arbitrary initial position and orientation. In order to achieve a collision-free and low cost motion, the moving path from initial position to final target had to be planned online. Because of the nonholonomic characteristic and the impact of obstacles, it is necessary to find appropriate sub-targets corresponding to each current state and map information until arrive at the final target.

C. Soft Target Setting Knowledge

In order to acquire the target setting knowledge for the current state, the $30m \times 15m$ space is described by occupancy grid maps with $2m$ interval as showed in Figure 7 in which each small circle denotes a target location (x, y) of robot (total 128 points). And the orientation θ is divided into eight azimuths $(0, 0.25\pi, 0.5\pi, 0.75\pi, \pi, 1.25\pi, 1.5\pi, 1.75\pi)$. Thus, the space results $128 \times 8 = 1024$ target candidates. For arbitrary state, we can approximate it to the nearest grid location and orientation. So it is possible to obtain all possible targets corresponding to the current state and obstacles information

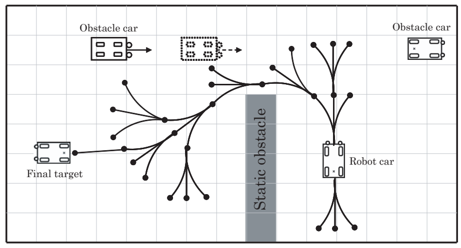


Fig. 6. Problem description

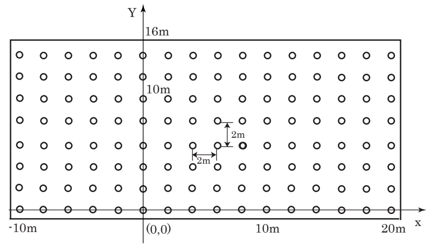


Fig. 7. Moving map for robot

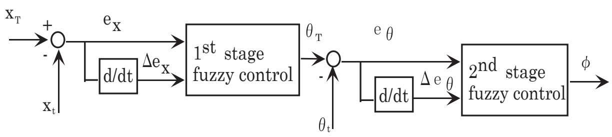
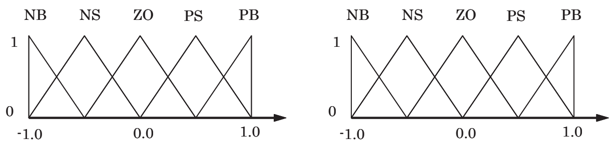


Fig. 8. Cascade fuzzy controller



(a) e_x / e_θ (b) Δe_x / Δe_θ

Fig. 9. Membership functions of cascade fuzzy controller

to form a state-action table with its action evaluation value named membership value in this study. This state-action table is defined as the soft target setting knowledge for the robot car. It is learned based on the final target, current state and obstacle information in real-time. The learning process is to find all possible sub-targets that can reach the final target directly.

In order to obtain the evaluation value of each target, we suppose the vehicle moving from an arbitrary position $r_i = (x_i, y_i, \theta_i)$ in the map to achieve the final target $r_{Final} = (x_{final}, y_{final}, \theta_{final})$ controlled by cascade fuzzy control method as showed in Figure 8. In which, the current target orientation θ_T is fuzzy inferred from deflection e_X of current position X_t and target X_T, then, operation steering angle ϕ is fuzzy inferred from error e_θ of the target direction θ_T and the current body direction θ_t. The membership functions used for evaluating e_X and e_θ are denoted in Figure 9. And the 1^{st} stage and 2^{nd} stage fuzzy inference models are denoted

TABLE I

1^{st} STAGE FUZZY INFERENCE MODEL

$\theta_T(rad)$		$e_X(m)$				
		NB	NS	ZO	PS	PB
Δe_X	NB	-2.5916	-2.4738	-2.356	-2.2382	-2.1204
	NS	-1.413	-1.2958	-1.178	-1.0602	-0.9424
	ZO	-0.2356	-0.1178	0.0	0.1178	0.2356
	PS	0.9424	1.0602	1.178	1.2958	1.4136
	PB	2.1204	2.2382	2.356	2.4738	2.5916

TABLE II

2^{st} STAGE FUZZY INFERENCE MODEL

$\phi(rad)$		$e_\theta(rad)$				
		NB	NS	ZO	PS	PB
Δe_θ	NB	7.0	4.5	2.0	-0.5	-3.0
	NS	6.0	3.5	1.0	-1.5	-4.0
	ZO	5.0	2.5	0.0	-2.5	-5.0
	PS	4.0	1.5	-1.0	-3.5	-6.0
	PB	3.0	0.5	-2.0	-4.5	-7.0

TABLE III

SOFT TARGET FOR FINAL TARGET$(-6m, 6m, 1.0\pi)$

Number	Sub-target position	Membership value μ
1	(0m, 2m, 0.5π)	0.774
2	(0m, 4m, 0.75π)	0.026
3	(0m, 4m, 1.0π)	0.009
⋮	⋮	⋮
65	(4m, 14m, -0.25π)	0.622
66	(-6m, 6m, 1.0π)	0.999
67	(6m, 0m, 0.0π)	0.395
⋮	⋮	⋮
351	(20m, 10m, 1.0π)	0.624
352	(20m, 12m, 1.0π)	0.568
353	(20m, 14m, 1.0π)	0.512

by Table I and Table II respectively.

The evaluation value $\mu_{\widetilde{T_n}}(r_i)$ is calculated according to the following cost functions.

$$\begin{aligned}
\mu_{\widetilde{T_n}}(r_i) &= \mu_{time}(r_i) \wedge \mu_{ope}(r_i) \wedge \mu_{err}(r_i) \\
\mu_{time}(r_i) &= (t_{max} - t)/t_{max} \in [0,1] \\
\mu_{ope}(r_i) &= 1.0 - \alpha \sum_{t=0}^{time} |ope(t)| \in [0,1] \\
\mu_{err}(r_i) &= \mu_{dx}(x) \wedge \mu_{dy}(y) \wedge \mu_{d\theta}(\theta) \in [0,1]
\end{aligned} \tag{4}$$

Where, $\mu_{time}(r_i)$ is evaluation of limit time, $\mu_{ope}(r_i)$ is evaluation of steering amount, $\mu_{err}(r_i)$ is evaluation of arrival grade to final target. t_{max} is the maximal limit time for a moving learning, t is the consumption time till arriving at the final target, $\sum_{t=0}^{time} |ope(t)|$ is the total steering amount, α is coefficient of it. $\mu_{dx}(x)$, $\mu_{dy}(y)$, $\mu_{d\theta}(\theta)$ are error evaluations of current position (x, y, θ) to final target respectively whose error evaluation membership functions are shown in Figure 10 The less the consumption time or total steering amount or error evaluations to final target, the higher the evaluation value of the alternative target. For those that are unable to reach the final target, the membership values are set as 0. For the first time, the soft target is learned in this map without considering any obstacle. Afer then, it is learned near the current position (it is set in the range of $8m$ from current position) to reduce the computation expense. If there is no available target for the current state, system selects the one learned at the first time as the soft target set.

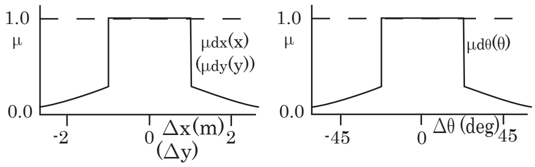


Fig. 10. Error evaluation membership functions

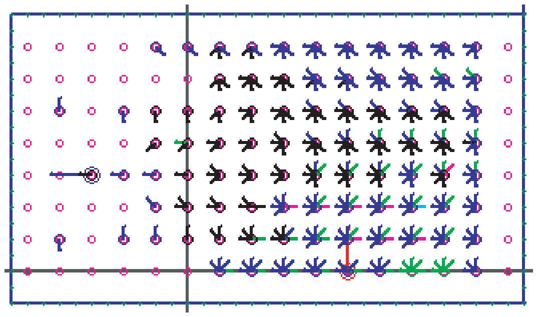


Fig. 11. Image of soft target for final target$(-6m, 6m, 1.0\pi)$ with $\mu \geq 0.1$

Based on the cost evaluation function (4), we can obtain each available sub-target and its membership value which presents its satisfactory degree. Table III lists the acquired soft target set for final target $(-6m, 6m, \pi)$ without considering any obstacle. There are 353 possible candidates in which $(-6m, 6m, \pi)$ has the highest evaluation value 0.999. Figure 11 denotes 209 candidates which have the membership value above 0.1. Here, the black cords denote the targets with the membership value above 0.7, the blue means the membership value is above 0.5, the green means the membership value is above 0.3, and the magenta means the membership value is above 0.1.

D. Soft Target Based PFC Intelligent Controller

The constructed system based on soft target and predictive fuzzy control is denoted as Figure 12.

Firstly, the current robot's pose and obstacles information are detected by the state detector part. By judging the attainment degree to the final target and the contact degree to the obstacles, it decides whether giving target setting instruction or not. If it is necessary to reset target, soft target for the current state and environment is learned to obtain all possible candidates.

Then, for each candidate r_i in $\widetilde{T_n}$, the control instruction C_{r_i} is calculated by the cascade fuzzy control mechanism described in the foregoing paragraph. And the future pose

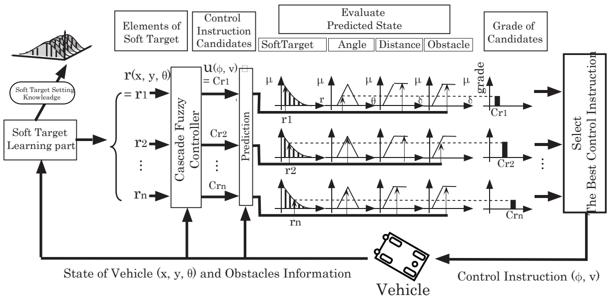


Fig. 12. Detail of the soft target based vehicle control system

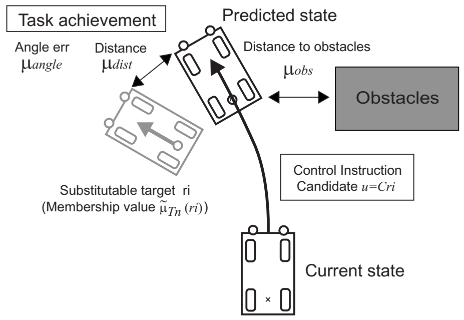


Fig. 13. Multipurpose fuzzy evaluation

$(x_{t+1}, y_{t+1}, \theta_{t+1})$ of robot is predicted for each instruction candidate C_{r_i} by the kinematics model (3).

Lastly, multipurpose fuzzy evaluation is carried out the for angle deflection between the predicted state and the target, distance deflection from the predicted pose to the target and the minimal distance to the obstacles as denoted in Figure 13. It calculates the evaluation values of all candidates and selects the one with the highest evaluation value as the control target to calculate relevant control instruction.

The evaluation value of the operation instruction candidate which results moving in the opposite direction is reduced a half to avoid the local minima problem.

IV. Simulation Results

In order to confirm the validity of the constructed control system based on soft target, we carried out four kinds of simulation: without any obstacle, with static obstacle, with moving obstacle and with static and moving obstacles. The simulation conditions are set as below.

- The parameters of the four-wheeled vehicle (assumed as about the size of an actual car) are: width of the car $b = 1.8m$, wheelbase $L = 2.6m$, minimal outside turning radius $R_{min} = 4.0m$, and the moving speed $v = 0.4m/s$ in both ahead and back.
- The map is set as Figure 7, and the static obstacle is placed at from $4m \leq x \leq 6m, 0m \leq y \leq 9m$.
- The moving obstacle car with the same size of the robot car moves at a speed of $0.4m/s$ from left to right with steering angle 0.

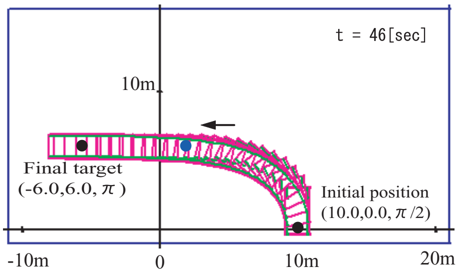


Fig. 14. Robot trajectory without obstacle

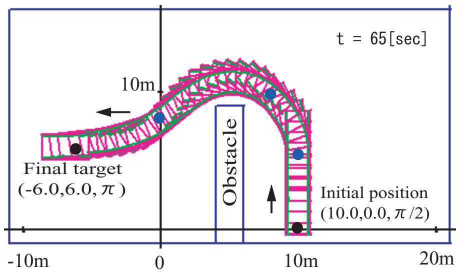


Fig. 15. Robot trajectory with static obstacle

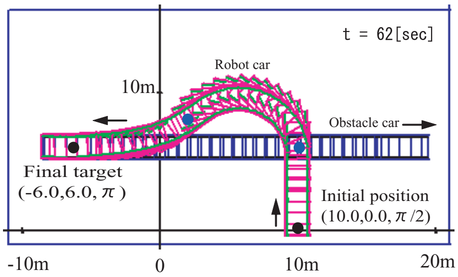


Fig. 16. Robot trajectory with dynamic obstacle

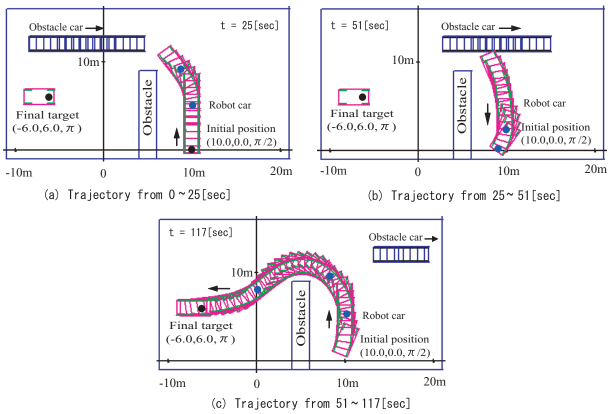


Fig. 17. Robot trajectory with static and dynamic obstacles

- Final target is set as $(-6m, 6m, \pi)$, and initial position is set as $(10m, 0m, 0.5\pi)$.

A. Without Any Obstacle

When there is no obstacle in the space, robot selects $(2m, 6m, \pi)$ with the membership value $\mu = 0.916$ as the best sub-target by learning and evaluation, and moves to final target by U-turns as denoted in Figure 14. The run time until arriving at final target is 46 seconds.

B. With Static Obstacle

Because of the impact of obstacle, the evaluation of sub-target $(2m, 6m, \pi)$ decreases, and robot selects the sub-goal $(10m, 6m, 0.5\pi)$ $(\mu = 0.556)$, $(8m, 10m, 0.75\pi)$ $(\mu = 0.644)$ and $(0m, 8m, -0.75\pi)$ $(\mu = 0.874)$ in turn by on-line learning to avoid the obstacle until it achieves the task finally. The run time until reaching the final state is 65 seconds. The running trajectory of robot car is showed in Figure 15.

C. With Moving Obstacle

The initial position of moving obstacle car is set as $(-8m, 6m, 0)$. By predicting and evaluating the future state of obstacle car and itself, robot selects $(10m, 6m, 0.5\pi)$ $(\mu = 0.556)$ as sub-target firstly, then selects $(2m, 8m, -0.75\pi)$ $(\mu = 0.849)$ to obtain the collision-free and low cost path. The running trajectory of it is denoted in Figure 16. The time of reaching the final target is 62 seconds.

D. With Static and Moving Obstacles

The initial position of moving obstacle car is set as $(-8m, 12m, 0)$. Firstly, robot selects $(10m, 6m, 0.5\pi)$ $(\mu = 0.556)$ and $(8m, 10m, 0.75\pi)$ $(\mu = 0.644)$ as sub-target to evade the static obstacle and approach to the final target. But before it reaches $(8m, 10m, 0.75\pi)$, it detects the moving obstacle car and had to reverse to guarantee the safety by selecting $(10m, 2m, 0.5\pi)$ $(\mu = 0.668)$ and $(8m, 0m, 0.25\pi)$ $(\mu = 0.544)$ as via-point in turn. After it detected that the near range is safe, it moves in the turns of sub-target $(10m, 6m, 0.5\pi)$ $(\mu = 0.556)$, $(8m, 10m, 0.75\pi)$ $(\mu = 0.644)$, $(0m, 8m, -0.75\pi)$ $(\mu = 0.874)$ till achieving the task. The running trajectory of it is denoted in Figure 17. The elapsed time until finally reaching is 117 seconds.

From these results, we confirmed that the robot controlled by this method can avoid the obstacles flexibly, and select the path with the lowest cost to achieve the task.

V. CONCLUSIONS

In this paper, a soft target based obstacle avoidance PFC intelligent controller for car-like mobile robot in a dynamic environment was proposed. The soft target defined as a set of all possible via-points is learned based on the final target, current state and environment information in real-time. For each element of it, we use predictive fuzzy control method to select the best one as the control target corresponding to the current state and environment. Based on the proposed soft target, it is possible to avoid obstacles (either static or dynamic) in the space flexibly without restriction of obstacle's placement and shape. And the final target can be set as we want because of the on-line learning of soft target.

The effectiveness of this method was demonstrated by the simulation results. A collision-free and low cost motion control of car-like mobile robot with the ability of dynamic environment self-adaptation was achieved. A new method simulating the decision process of human for moving body in dynamic environment was expored.

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