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Fuzzy Target Based Soft Decision for Mobile Vehicle in Dynamic Environment

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***Abstract*—This paper addresses the problem of real time flexible operation of a mobile vehicle in dynamic environment which is still a very challenging problem because the surrounding situations are not qualified in static, knowledge is only partial and the execution is often associated with uncertainty. It is difficulty to select appropriate sub-target in real-time to obtain a collision-free and low cost path. A conventional control method usually sets only a best control target beforehand based on the control purpose and object's characteristics. For many real systems, the situations always change with constraints or disturbances, which result in the necessary to set sub-targets between current state and final target. Thus recalculation of new target is necessary if the best target becomes unavailable because of the constraints or disturbances. And the recalculation is costly and involves time lags. Human decisions to act are based on broad targets and respond flexibly in different situations. Responding flexibly to the dynamic environment change like human is considered in this paper. We propose a fuzzy target based intelligent soft decision-making predictive fuzzy controller for differential drive mobile vehicle in dynamic environment to realize autonomous navigation. Simulation in Webots demonstrated the validity and feasibility of our fuzzy target based soft decision controller.**

***Index Terms*—fuzzy target, soft decision, predictive fuzzy control (PFC), diffirential drive mobile vehicle**

I. Introduction

The most basic navigation goals for a mobile vehicle can be summarized as (i) obstacle avoidance and (ii) target point reaching. It can be typically formulated as planning a path between two specified locations (initial and goal point), which is collision-free and satisfies certain optimization criteria.

Many methods for mobile vehicle's autonomous navigation have been proposed, such as behavior-based navigation [1], fuzzy decision making theory [2], potential force field method [3], and so on, and significant results have been obtained in the past decades [4,5,6]. Many of the existing methods, however, to our knowledge, are more or less inflexibility in responding to changes in the environment and poor to respond to uncertainties, or rely on some knowledge of the global environment.

A 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 space 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.

A conventional control method usually uses a single best target that results in inflexibility in responding to dynamic environments. As shown in Figure 1, reacquisition of new target is necessary when the best target becomes unavailable because of constraints or disturbances. And the reacquisition

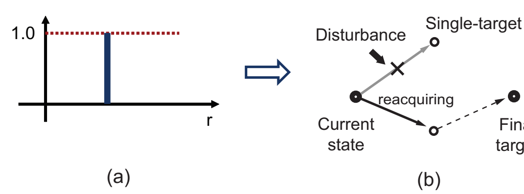

Fig. 1. Image of single-target and its utilization

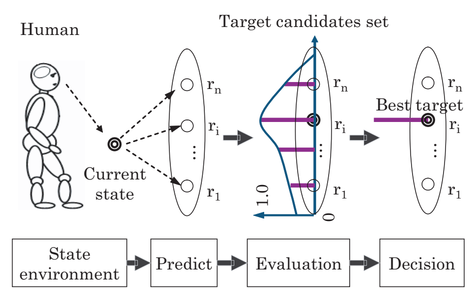

Fig. 2. Decision process of human

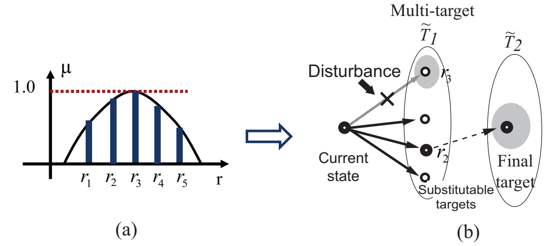

Fig. 3. Image of multi-targets and its utilization

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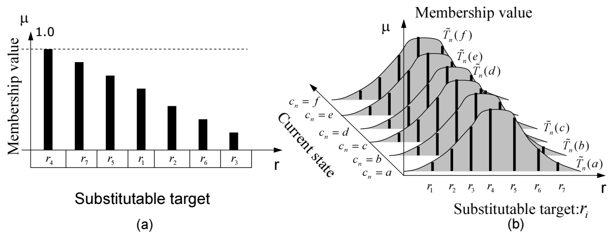


Fig. 4. Definition of fuzzy target

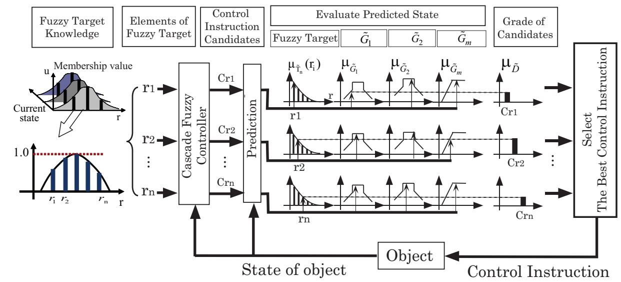


Fig. 5. Fuzzy target based PFC soft decision process

is costly and involves time lags.

Human's action decision (Figure 2) is based on multi-targets and can respond flexibly under different situations just based on information which are intrinsically vague, imprecise and fuzzy. The best alternative target is selected in real time based on experiences by predicting and evaluating the state of the object with taking dynamic environment information into account. From the process of human decision, we can know it is the multi-targets based methodology that results in their dynamic soft decision and flexibility. As denoted in Figure 3, when disturbances make the best target r_3 in multi-target set with membership 1.0 become unavailable, system selects the suboptimal target r_2 as control target automatically to respond to situation change in environment flexiblely.

In this research, the multi-targets are regarded as "fuzzy target" set. And we propose a fuzzy target based intelligent soft decision-making PFC (predictive fuzzy control) controller to realize a flexible autonomous operation like human for a differential drive mobile vehicle in a dynamic environment.

II. Soft Decision with Fuzzy Target

A. Fuzzy Target

Fuzzy 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 [8].

It is denoted as Figure 4(a), and can be expressed by the membership function of enumeration type.

The total set of the target is assumed as R. fuzzy 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 fuzzy 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 4(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 fuzzy 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 decision-making.

B. Soft Decision by Predictive Fuzzy Control

Decision making problems are described as choosing an action from possible alternatives using available information [9]. Soft decision-making applies approximate reasoning and incomplete or uncertain information to find a fuzzy set of best decision alternatives.

In a discrete decision space, let $R = \{r_1, r_2, \cdots r_n\}$ be the set of decision alternatives, $\tilde{G}_j (j = 1, \cdots m)$ be the fuzzy sets representing different control goals (or constraints). When the attainment of the goal G_j by alternative r_i can be expressed by the degree of membership $\mu_{\tilde{G}_j}(r_i)$, the decision set $\tilde{D}$ can be acquired as

$$\tilde{D} = \tilde{G}_1 \cap \tilde{G}_2 \cap \cdots \cap \tilde{G}_m \tag{2}$$

Based on the acquired fuzzy target, soft decision is made by predictive fuzzy control to simulate the process of human decision [10]. The soft decision-making process are described as Figure 5.

Firstly, a fuzzy target set are select corresponding to the current strate from the learned fuzzy target knowledge. And each element of it is assumed as the control target to calculate the operation instruction candidates. 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 as equation (3). More generally, we may express $\mu_{\tilde{D}}$ as equation (4), where weight coefficient α_j can be chosen in such a way to reflect the relative importance of each control goal G_j. It is true of the real system since each control goal usually has different weight. The evaluation value of the operation instruction candidate is calculated by (3) or (4). Lastly, the operation instruction candidate with the highest evaluation value is selected as the current control instruction.

$$\mu_{\tilde{D}} = \mu_{\tilde{G}_1} \wedge \mu_{\tilde{G}_2} \wedge \cdots \wedge \mu_{\tilde{G}_n} \tag{3}$$

$$\mu_{\tilde{D}} = \sum_{j=1}^{m} \alpha_j \cdot \mu_{\tilde{G}_j} \qquad \sum_{j=1}^{m} \alpha_j = 1 \tag{4}$$

These operations are repeated in the whole control process until achieving the final target. Thus, the soft decision based on fuzzy target is realized.

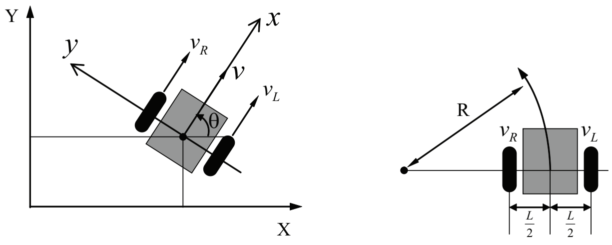


Fig. 6. Model of diffrential drive mobile robot

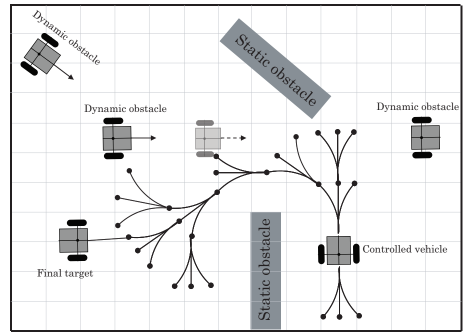


Fig. 7. Problem description

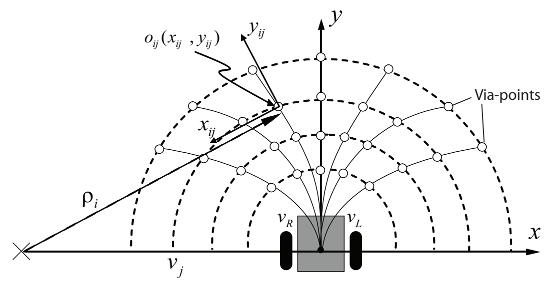


Fig. 8. Via-points defined as fuzzy target

III. Application to Mobile Vehicle in Dynamic Environment

A. Characteristics of Differential Drive Mobile Vehicle

The configuration of a two-wheeled differential drive vehicle (Figure 6) can be denoted by $q = [x, y, \theta]^T \in \mathbb{R}^3$. Where, (x, y) is the Cartesian location of the center of its wheels, θ is orientation of the vehicle which defined as the heading angle between the body axis and the horizontal axis. v_R and v_L are linear velocity of right and left wheel respectively. L is the width of car. r is wheel radius. R is turning radius defined as the distance between instantaneous center of curvature to centerline of the vehicle. Choosing the control input $U = [v, \omega]^T$, the kinematic equation yields:

$$\dot{q} = \begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} = \begin{pmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v \\ \omega \end{pmatrix} \tag{5}$$

$$\begin{aligned} v &= \frac{v_R + v_L}{2} = \frac{(\omega_R + \omega_L) \cdot r}{2} \\ \omega &= \frac{v_R - v_L}{L} = \frac{(\omega_R - \omega_L) \cdot r}{L} \end{aligned} \tag{6}$$

where, v is linear velocity of the vehicle, ω is angular velocity of the vehicle. ω_R and ω_L are angular velocity of right and left wheel respectively. Obviously, (3) is a so-called driftless nonlinear system with 2 inputs (v, ω) and 3 outputs (x, y, θ) constrained by $\dot{x}\sin\theta - \dot{y}\cos\theta = 0$ which means no slip occurs in the orthogonal direction of rolling. From these equations, we can know the vehicle's posture is controlled in nature by ω_R and ω_L.

B. Problem Description

We considered a differential mobile vehicle pioneer2^{TM} with 16 ultrasonic sensors around its body moving in a 2D indoor space as denoted in Figure 7, where the vehicle has no a priori knowledge of either static or dynamic obstacles in its environment. 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 vehicle can start at arbitrary initial position and orientation.

The navigation can be modeled as decision-making of the most appropriate via-point (fuzzy targets) among the numerous possible paths to satisfy its navigation goals, such as collision-free and low cost(reach target as fast as possible). The fuzzy targets are acquired corresponding to each current state considering the vehicle's motion capability and constraints. In order to achieve the final target with the control goals of collision-free and low cost, the moving path from initial position to final target had to be planned online. Because of the impact of obstacles and changes in environment, it is necessary to find appropriate sub-targets corresponding to each current state and constraints until arriving at the final target.

C. Fuzzy Target Setting Knowledge

The target setting knowledge is a series of fuzzy sets of all available via-point corresponding to current state as showed in Figure 8 [11]. Via-point is defined as the sub-target point of vehicle's movement at each decision instance. These next via-points can be considered as the alternatives of vehicle's next movement. Candidates of next via-points of the wheeled mobile vehicle $o_{ij}(x_{ij}, y_{ij})$ are determined by a pair of path curvature (or radius of curvature) and linear velocity (ρ_i, v_j). Though pioneer2^{TM} with sensors around its body, considering the safety and vehicle's motion capability, a total of 20 curvature candidates in the front side and 3 velocity candidates are selected which results 60 via-point candidates (x_{ij}, y_{ij}). All possible candidates are learned based on the final target, current state and obstacle information in real-time.

In order to obtain the membership value of each via-point, we suppose the vehicle moving from an arbitrary position $r_i = (x_i, y_i, \theta_i)$ in the 60 via-points candidates to achieve the final target $r_{Final} = (x_{final}, y_{final}, \theta_{final})$ controlled by cascade fuzzy control method as showed in Figure 9 without considering any obstacle. In which, the current target

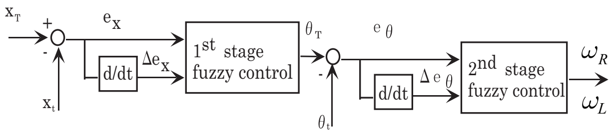
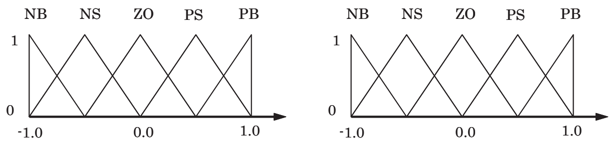


Fig. 9. Cascade fuzzy controller



(a) e_x / e_θ (b) Δe_x / Δe_θ

Fig. 10. Membership functions of cascade fuzzy controller

orientation θ_T is fuzzy inferred from deflection e_X of current position X_t and target X_T, then, angular velocity of right and left wheel (ω_R and ω_L)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 10.

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

$$
\begin{aligned}
\mu_{\widetilde{T_n}}(r_i) &= \mu_{time}(r_i) \wedge \mu_{ope}(r_i) \wedge \mu_{err}(r_i) \\
\mu_{time}(r_i) &= (t_{max} - t)/t_{max} \in [0,1] \\
\mu_{ope}(r_i) &= 1.0 - \alpha \sum_{t=0}^{time} |ope(t)| \in [0,1] \\
\mu_{err}(r_i) &= \mu_{dx}(x) \wedge \mu_{dy}(y) \wedge \mu_{d\theta}(\theta) \in [0,1]
\end{aligned}
\tag{7}
$$

Where, $\mu_{time}(r_i)$ is evaluation of limit time, $\mu_{ope}(r_i)$ is evaluation of heading angle change 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 heading angle change 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 11 The less the consumption time or total heading angle change 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.

Based on the cost evaluation function (4), we can obtain each available sub-target and its membership value which presents its satisfactory degree.

D. Fuzzy Target Based Soft Decision-Making

The constructed PFC soft decision-making system based on fuzzy target for the differential mobile vehicle can be outlined as Figure 12. It is composed of three parts: state detecting part, fuzzy target setting part and decision making part.

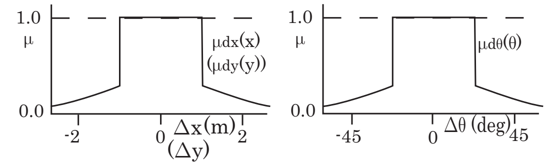


Fig. 11. Error evaluation membership functions

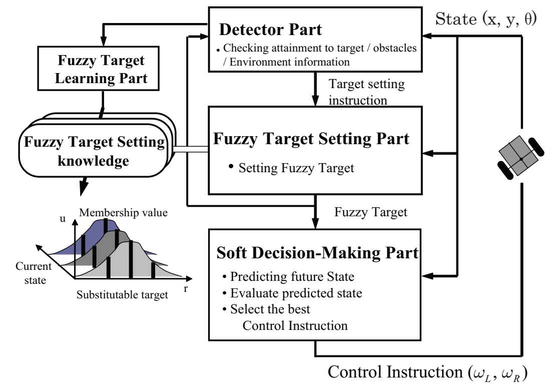


Fig. 12. Outline of the soft decision control based on fuzzy target

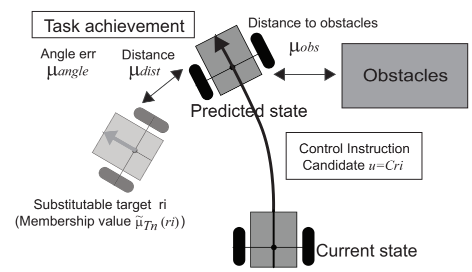


Fig. 13. Multipurpose fuzzy evaluation for soft decision

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

2) Fuzzy Target Learning Part: For the 60 via-point candidates, acquire their membership values corresponding to the current strate and environment information to prepare the fuzzy target setting knowledge for next sampling time.

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

4) Soft Decision-Making Part: For each candidate r_i in $\widetilde{T_n}$, the control instruction C_{r_i} is calculated by the cascade fuzzy control mechanism as Figure 9. And the future posture

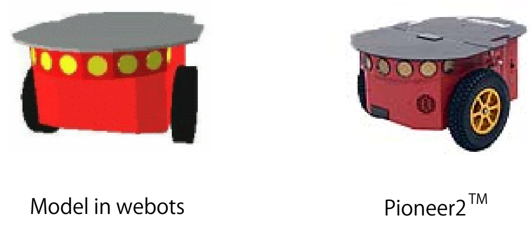


Fig. 14. Model in Webots and real robot

$(x_{t+1}, y_{t+1}, \theta_{t+1})$ of vehicle is predicted for each instruction candidate C_{r_i} by the kinematics model (5). Then multipurpose fuzzy evaluation is conducted for angle deflection, distance deflection and the minimal distance to obstacles (Figure 13). It calculates the evaluation values of all candidates and make decision to select the one with the highest evaluation value as the control target by the following equation.

$$\begin{aligned} \mu_{\tilde{D}} &= \alpha_1 \cdot \mu_{\tilde{T}_n}(r_i) + \alpha_2 \cdot \mu_{angle}(\theta) \\ &+ \alpha_3 \cdot \mu_{dist}(x, y) + \alpha_4 \cdot \mu_{obs}(\delta) \end{aligned} \tag{8}$$

here, $[\alpha_1, \alpha_2, \alpha_3, \alpha_4]^T = [0.1, 0.2, 0.3, 0.4]^T$.

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 in Webots

In order to confirm the validity of the constructed soft decision control system based on fuzzy target, we carried out simulation in Webots with the model of pioneer2^{TM} (Figure 14) which has 16 ultrasonic sensors around its body [12]. We carried out two kinds of simulation: with static obstacle and with static and moving obstacles. The simulation conditions are set as below.

- The parameters of pioneer2^{TM}: width of the car $L = 0.3206m$, wheel radius $r = 0.0825m$.
- The map is set as a $3m \times 3m$ 2D space, and the static obstacle is placed arbitrarily.
- The moving obstacle vehicles with the same size of pioneer2^{TM} move at a real time changing random angular velocity which results their moving heading angles are changing momentarily too.
- 20 radius of curvature candidates in the front side are set as equality in $(-4m, 4m)$ and 3 velocity candidates are set as $0.1m/s$, $0.25m/s$, and $0.5m/s$.
- Final target is set as $(1.2m, 1.2m, \pi/2)$, and initial position is set as $(-1.2m, -1.2m, \pi)$.

A. Moving in Static Environment

There are only three static obstacles placed arbitrarily in the space. The vehicle moved smoothly near the central of coordinate, then detected obstacle in front, so choose turning a little to the right to approach to the final target. The run time until reaching the final state is 18.7 seconds. The running trajectory of vehicle is showed in Figure 15. Figure 16 is snapshot in Webots.

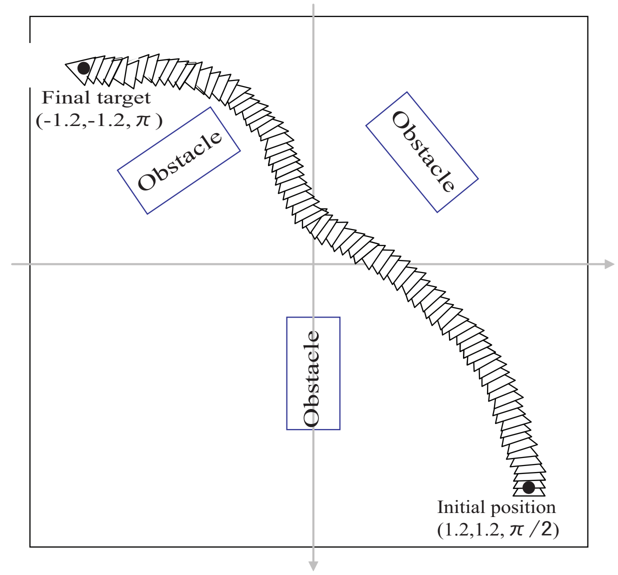


Fig. 15. Trajectory with static obstacle

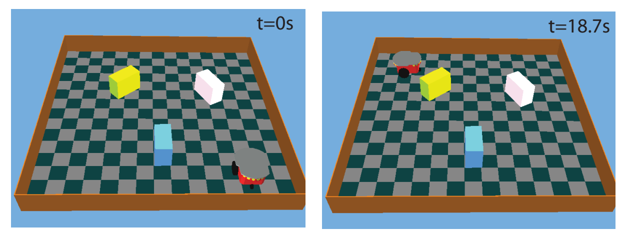


Fig. 16. Snapshot of moving in static environment

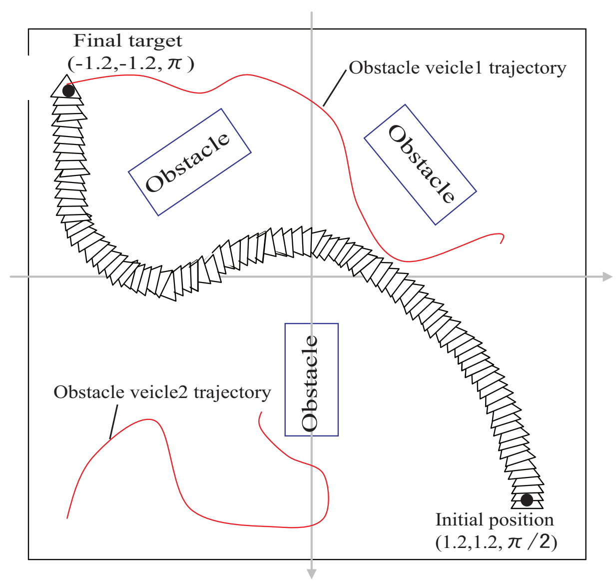


Fig. 17. Trajectory with static and dynamic obstacles

B. Moving in Dynamic Environment

There are 2 moving obstacles in the space besides 3 static obstacles. Because of the impact of moving obstacles, the

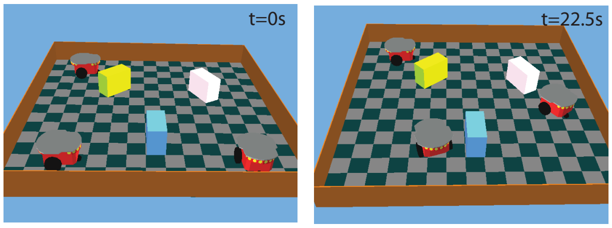


Fig. 18. Snapshot of moving in dynamic environment

controlled vehicle choose the turning left to avoid the moving obstacle 1 at about the central of coordinate. As we presume the vehicle unable to moving back which means the angular velocity of left and right wheel won't be minus, although the vehicle reach the final target position, the orientation error is too big to stop and give target achieve instruction, which resulted in the vehicle continued its navigation. It is possible to solve this problem in the next stage by considering the back sensors' data to permit the vehicle moving back. The running trajectory is denoted in Figure 17. Figure 18 shows the 3D moving snapshot in Webots. The elapsed time until finally reaching is 22.5 seconds.

From these results, we confirmed that the mobile vehicle controlled by this method can achieve final target quickly as well as avoid the obstacles flexibly by making decision to select the appropriate via-points.

V. Conclusions

A new intelligent PFC soft decision-making for diffirential drive mobile vehicle motion control in a dynamic environment was proposed. The fuzzy target is defined as a set of all possible via-points which are 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 make soft decision to select the best one as the control target corresponding to the current state and environment. Based on the proposed fuzzy target, it is possible to achieve any final target avoiding obstacles (either static or dynamic) in the space flexibly without restriction of obstacle's placement and shape.

The effectiveness of this method was demonstrated by the simulation in Webots. A collision-free and low cost motion control of mobile vehicle with the ability of dynamic environment self-adaptation was achieved. A new method simulating the decision process of human for moblie body in dynamic environment was explored.

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