Fuzzy Tracking Method with a Switching Grey Prediction for Mobile Robot

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Abstract

A mobile robot fuzzy tracking mechanism for the mobile robot is proposed in this paper. A switching grey prediction is proposed such that the mobile robot can track the target effectively. Conventional position based tracking strategies usually define the dynamics models for either motion control on tracker or position prediction on target, this makes the system inflexible and difficult to implement. Our fuzzy tracking systems based on switching grey prediction can be extended as a flexible strategy in dealing with the uncertain environment in robotics applications. The grey prediction attempts to establish a grey model from the recently historical information. The model is updated online as the input changed. According to the grey model, the switching mechanism can adjust the forecasting step-size for prediction. The performances of the simulated are presented. It is clear that the proposed tracking systems are available and effective.

1 Introduction

RoboCup is an attempt to promote intelligent robotics research by providing a common task for evaluation of various theories, algorithms, and agent architectures. The First Robot World Cup Soccer Games and Conferences were held during the International Joint Conference on Artificial Intelligence at Nagoya. Until recently, a series of technical workshops and competitions have been planned for the future [1-4]. In the RoboCup, each player has to make quick decisions reactively and rationally in any game situations. Many artificial intelligence methods exist for path planning, based on tools like, genetic algorithms [5-7], the artificial potential field [8], and artificial neural network [9]. This highly dynamic environment makes many traditional motion planning algorithms impractical since the environment changes before the planner can even finish it's path. The welding process complex dynamics, non-linearity, and time variance render traditional control system techniques difficult to apply. Target tracking is very important topic in the robot soccer game. For a general position-based tracking task, prediction of the object position from noisy sensory measurements is required to solve. Most of the existing approaches for the target tracking system need a complex kinematics model of the target for prediction. It is difficult to apply. This paper presents a fuzzy tracking system with a switching grey prediction. The block diagram of the system is shown in Fig. 1. Grey prediction and fuzzy theory have been successfully applied in many fields recently [10, 11]. The remainder of this paper is organized as follows: Section 2 describes the tracking system based on fuzzy theory. In Section 3, switch target position prediction is described, and the performance of the proposed system is simulated in Section 4, Summary and suggestions for future research are included in Section 5.

2 Fuzzy tracking system

The related parameters between the robot and the ball are described in Fig. 2, where (x, y) is the coordinate of the center of the mobile robot, V is the mobile robot linear velocity, which has been considered constant, ϕ is the angle between the forward vector of the robot soccer and the horizontal vector, γ is the angle between the vector of the mobile robot to the ball and the horizontal vector, and ω is the angular velocity of the mobile robot. The dynamic model of the robot soccer can be expressed as

$$\begin{bmatrix} \dot{x}(t) \\ \dot{y}(t) \\ \dot{\phi}(t) \end{bmatrix} = \begin{bmatrix} \cos(\phi) & 0 \\ \sin(\phi) & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} V \\ \omega \end{bmatrix} \tag{1}$$

To determine the angular velocity ω, fuzzy theory is employed. In our system, the angular velocity of the mobile robot ω is decided using a fuzzy system according to the relationship between the ball and the mobile robot. The antecedent part of fuzzy rules uses two variables: d and θ, where d is the distance between the ball and the mobile robot location, while $\theta = \phi - \gamma$ is the angle which mobile robot has to rotate. If this difference is negative, the direction of the angular velocity ω is anticlockwise. If this difference is positive, the direction of the angular velocity ω is clockwise. In this paper, the angular velocity ω is assumed to be negative when the direction is clockwise.

In this fuzzy system, the distance d has three linguistic values (**N**- near, **M**- medium and **F**- far), and the angle θ has seven linguistic values (**NB**- negative big, **NM**- negative medium, **NS**- negative small, **ZE**- zero, **PS**- positive small, **PM**- positive medium and **PB**- positive big). The angular velocity ω is the consequent variable of the fuzzy rules and takes seven linguistic values (**NB**, **NM**, **NS**, **ZE**, **PS**, **PM** and **PB**). The membership functions of each linguistic values and range for each fuzzy variable are described in Fig.3, where the triangular and singleton are respectively used to describe the antecedent and consequent fuzzy sets. The triangular membership is specified by three parameters $\{a, b, c\}$ as follows:

$$triangle(x; a, b, c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0, & c \le x \end{cases}. \tag{2}$$

The fuzzy rule base is shown in TABLE I, where 21 fuzzy rules are employed to decide the rotational velocity of the mobile robot. The defuzzification process uses the center of gravity method.

3 Target Position Prediction

3.1 Grey Prediction theory

Prediction of the object position is a common mean for tracking a moving object. Accurate prediction usually leads the mobile robot achieving the desired rapidly. To predict the target position, there are also algorithms existed to calculate all the position, velocity, and acceleration of the moving target from sensory measurement. However, in many control system applications, the flexibility of the prediction will be reduced due to the use of the complicated dynamic model of the plant. The grey prediction assumes the internal structure, parameters, and characteristics of the observed system are unknown. It attempts to establish a grey model from the recently historical measurements of the external motion. The grey prediction needs less number of existing sensory measurements and can predict the next trend of target. The concept of the grey predictor is briefly described as follows:

Let $y^{(0)}$ be a non-negative original data sequence,

$$y^{(0)} = \{y^{(0)}(1), y^{(0)}(2), \ldots, y^{(0)}(n)\}, \quad n \geq 4 \tag{3}$$

and take the accumulated generating operation (AGO) on $y^{(0)}$, then the first order AGO sequence $y^{(1)}$ can be described by

$$y^{(1)}(k) = \text{AGO} \circ y^{(0)} \equiv \sum_{m=1}^{k} y^{(0)}(m), k = 1, 2, \ldots, n. \tag{4}$$

and the sequence $z^{(1)}$ can be obtained by applying the MEAN operation to $y^{(1)}$,

$$z^{(1)}(k) = \text{MEAN} \circ y^{(1)} \equiv \frac{1}{2}[y^{(1)}(k) + y^{(1)}(k-1)], \quad k = 2, 3, \ldots, n. \tag{5}$$

The data generating operating operations, AGO and MEAN operations, are the first step in building the grey model. By the way, AGO can weak the randomness of the row data to generate a regular sequence $y^{(1)}$.

The equation

$$y^{(0)}(k) + az^{(1)}(k) = u_g \tag{6}$$

is called a grey differential equation of GM(1,1), where the parameters a and u_g are called the development coefficient and the grey input, respectively. The equation

$$\frac{dy^{(1)}}{dt} + ay^{(1)} = u_g \tag{7}$$

is called the whitening equation corresponding to the grey differential equation of Equation (6). In order to find out the solution of the above differential equation, the parameters a and u_g must be decided. They can be solved by means of the least-square method as follows:

$$\hat{\theta} = \begin{bmatrix} a \\ u_g \end{bmatrix} = \left(B^T B\right)^{-1} B^T y^N, \tag{8}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & 1 \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{9}$$

and

$$y^N = [y^{(0)}(2)\, y^{(0)}(3) \cdots y^{(0)}(n)]^T. \tag{10}$$

Since the solution of the whitening equation (7) is

$$y^{(1)}(t) = (y^{(0)}(1) - \frac{u_g}{a}) \cdot e^{-a(t-1)} + \frac{u_g}{a} \tag{11}$$

the solution of the corresponding grey differential equation can be expressed by

$$\hat{y}^{(1)}(n+p) = (y^{(0)}(1) - \frac{u_g}{a}) \cdot e^{-a(n+p-1)} + \frac{u_g}{a}, \quad n \geq 4 \tag{12}$$

where the parameter "p" is the forecasting step-size and the upscript "^" means the value $\hat{y}$ is a forecasting value of y. Take the sequence $\hat{y}^{(0)}$ can be determined by taking the inverse AGO (IAGO) on $\hat{y}^{(1)}$ and described by

$$\hat{y}^{(0)}(k) = IAGO \circ y^{(1)} = \hat{y}^{(1)}(k) - \hat{y}^{(1)}(k-1), \quad k = 2, 3, \ldots, n \tag{13}$$

Therefore, the forecasting value of $y^{(0)}(n+p)$ can be expressed by:

$$\hat{y}^{(0)}(n+p) = (y^{(0)}(1) - \frac{u_g}{a}) \cdot e^{-a(n+p-1)} \cdot (1 - e^{a}), \quad n \geq 4 \tag{14}$$

Based on the above description, the grey predictor is constructed by AGO, IAGO, and GM(1,1) and is described by

$$\hat{y}^{(0)} = IAGO \circ GM(1,1) \circ AGO \circ y^{(0)}. \tag{15}$$

3.2 Switching Grey Prediction

In order to catch up to the moving ball efficiently, the future ball position that the robot will be reached must be considered. The fuzzy tracking method described in Section 2 is difficult to adjust the direction under sudden changes such as bounced ball from the wall. On the other hand, if the future ball position can be predicted, then that the robot can catch up to the moving ball rapidly. Using grey predictor to predict the future ball position is a good way to solve this problem. In the grey predictor the forecasting step-size decides the forecasting value. If the robot far from the ball it will spend much time to reach the ball. The distance between the ball and the robot is considered here that the forecasting ball position of the output will be changed depend on it. Therefore, we use a switching mechanism to switch the forecasting step-size to integrate the advantages. In addition, we find proper forecasting step-sizes to speed up the time of the robot reach target. The configuration of the proposed control structure is shown in Fig. 1, where the switching mechanism is defined by

$$p = \begin{cases} p_l & \text{if } d > d_l \\ p_m & \text{if } d_m < d \leq d_l \\ p_s & \text{if } d_s < d \leq d_m \\ 0 & \text{if } d < d_s \end{cases} \tag{16}$$

where p is the forecasting step-size of the system; p_l, p_m and p_s are the forecasting step-sizes for the large output, the middle output and the small output, respectively; d_l, d_m and d_s are the distance between ball and car of the large, the middle and the small, respectively.

4 Simulations

To demonstrate the effectiveness of the proposed method, two types of evens are simulated. (a). The ball didn't hit the wall during the tracking. (b). The ball hit and rebounded off the wall during the tracking. One curve in the figure is the tracking path of a mobile robot (Robot-1) with the switching grey prediction; the other one is the tracking path of a mobile robot (Robot-2) without the prediction. In the simulations, the following parameter values are considered: car length=80, robot width=80, robot velocity=20, friction=0.2. Because the friction, the ball will get slower.

The simulation results for Type (a) are shown in Fig. 4. The first case in Fig. 4(a), the two cars started at the same position. The Robot-1 with the switching grey prediction could predict the ball position at once, and caught up to the moving ball first. In Fig. 4(b), the distance between the ball and the Robot-1 is farther than that between the ball and the Robot-2. The Robot-1 could predict the future ball position and still catch up the moving ball earlier. It is the effectiveness of the proposed method.

The simulation results for Type (b) are shown in Fig. 5. In Fig. 5(a), the two robots started at the same position. The Robot-1 catches up to the moving ball earlier. In Fig. 5(b), the distance between the ball and the Robot-1 is further than that between the ball and the Robot-2. The switching grey prediction robot could predict that ball would hit the wall. Hence, the Robot-1 goes toward the predicted ball position and caught up to the moving ball earlier.

5. Conclusions

A fuzzy tracking system based on switching grey predictive is presented in this paper. Comparing with the conventional target tracking strategies, the switching grey prediction can update the system dynamics model parameters according to limited information. The comparison of our proposed method with tracking path without switching grey prediction for the same plant are shown in Fig. 4 and Fig. 5. We can find that the proposed fuzzy tracking system based on switching grey prediction can be extended as a flexible strategy in dealing with the uncertain environment in robotics applications. From the above comparison, it is clear that the proposed tracking system is available.

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TABLE I

Fuzzy rule base

ω		d		
		N	M	F
θ	NB	PB	PM	PS
	NM	PB	PS	PS
	NS	PS	PS	ZE
	ZE	ZE	ZE	ZE
	PS	NS	NS	ZE
	PM	NM	NS	NS
	PB	NB	NM	NS

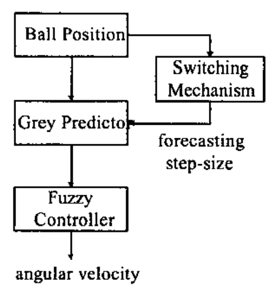


Fig. 1. Block diagram of the switching grey prediction fuzzy tracking system

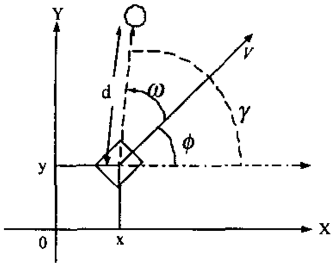
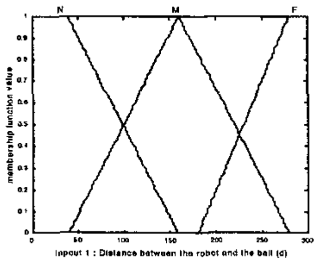
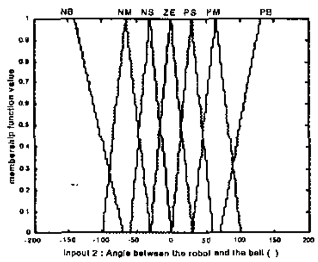


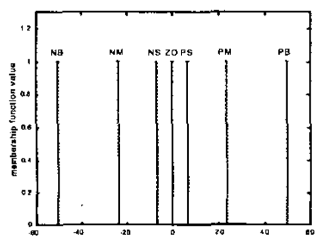
Fig. 2. The relationship between the ball and the robot



(a)

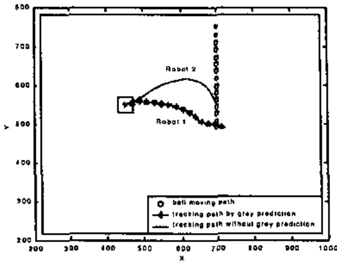


(b)

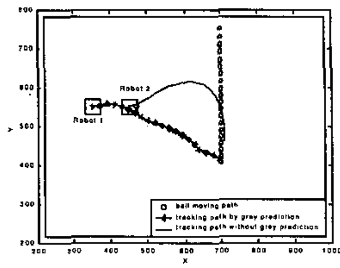


(c)

Fig. 3. Fuzzy sets for the tracking control system (a) Input: Membership function for d (b) Input: Membership function for (c) Output: membership functions for ω

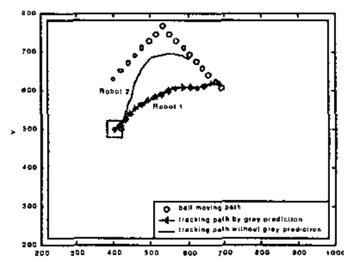


(a)

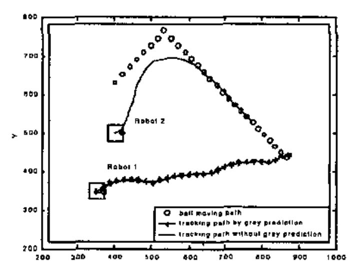


(b)

Fig. 4. Tracking Paths of Robot 1 (with grey prediction) and Robot 2 (without grey prediction) for three situation: (a) two robots were at the same position. (b) Robot 2 is ahead of the Robot 1.



(a)



(b)

Fig. 5. Where the ball rebounded off the wall during the tracking (a) two robots are at the same position. (b) Robot 2 is ahead of the Robot 1.