An Intelligent Predictive Control Approach to Path Tracking Problem of Autonomous Mobile Robot

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ABSTRACT

An intelligent predictive control approach to the path tracking problem of autonomous mobile robot is presented based on the analysis of the characteristics of the vehicle model and the traditional predictive control algorithm. A neural network model of the vehicle is used to predict future vehicle posture according to the current posture and control variables. The future tracking error between this predictive posture and the planned ideal path created by the local path planning module can be calculated. The optimal control variables in the next control instant are computed by the online optimization algorithm. The above process is updated and solved repeatedly. The intelligent predictive controller is composed of four principal components: a reference path, a predictive model, a set of online optimization algorithm and a feedback tuning model, which are discussed in detail in this paper. The characteristic of this method is analyzed and the result is provided.

1. INTRODUCTION

Large strides have recently been made in the research of Autonomous Mobile Robot (AMR), or named Autonomous Land Vehicle (ALV). Many prototypes have emerged such as the NavLab series [1][2] in USA, the VaMoRs[3] and the Caravelle [4] in Germany and the 7B8 and the THMR-III [5] in China. The AMR navigation system comprises many modules such as global path planning module, visual information processing module, information fusion module, positioning module, local path planning module and vehicle control module. The vehicle control module plays an important role in autonomous mobile robot navigation because it is the link of high-level intelligence such as perception, planning and inference and low-level performance such as steering and accelerating. The task of this module is to calculate the suitable steering angle and speed command based on the local path planning result and the current vehicle posture. In many cases, it can be expressed as a path tracking algorithm. It is a challenging problem because the robot vehicle is a nonlinear MIMO system with nonholonomic constraints. It has been a particularly active area of research and many methods have been proposed. In [6], PID algorithm is used to control the steering angle of the front wheel. The feedback of vehicle position and vehicle posture angle are compared with the planned ideal path then the errors can be obtained, which are also the input variables of the PID algorithm. After calculation, the output steering angle is sent to the implementation module. Nonlinear decoupling controller and pole-placement are used in [7] to obtain a closed-loop behavior that is independent of the vehicle operation point. Due to the steady state errors imposed by the nonlinear controller, a predictive filter is used to calculate the steady state error. In [8], a fuzzy controller is used to control the vehicle. Preview control is used in [9] and [10] where the optimal preview control algorithm is applied to the lateral guidance of a vehicle. The preview control algorithm is obtained by minimizing a quadratic performance index which includes terms representing the lateral tracking error as well as the oscillation of the vehicle. The results indicate that the tracking performance is improved by preview relative to that calculated for an algorithm without preview.

Predictive methods have gained wide popularity in industrial process control due to the possibility of reformulating the control problem as an optimization problem in which many physical constraints and nonlinearities can be allowed for [11][12][13]. In this paper, an intelligent predictive control strategy is presented based on the analysis of the characteristics of the vehicle model and the traditional predictive control algorithm. Put it briefly, the algorithm in this strategy can first use a neural network model of the vehicle to predict

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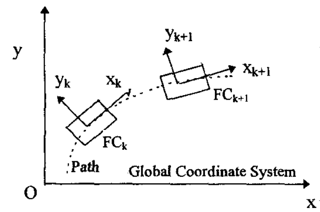
the future vehicle posture according to the current posture and manipulating variables. Second it can calculate future tracking error between the predictive posture and the planned ideal path created by local path planning module. Then the online optimization algorithm can obtain the optimal manipulating variables in the next control period. The above process is updated and solved repeatedly. The intelligent predictive controller comprises four principal components: a reference path, a predictive model, a set of online optimization algorithm and a feedback tuning model, which are discussed in detail in this paper.
The remainder of this paper is organized as follows: In Section II, an intelligent predictive controller is designed based on the analysis of vehicle driving features. Four principal components of the intelligent predictive controller are discussed in Section III. The characteristics of the reference path, the predictive model, the online optimization algorithm and the feedback tuning model are analyzed in this section. The intelligent predictive controller has been successfully applied to our THMR-III outdoor autonomous mobile robot. The result is shown in Section IV. The paper concludes with Section V where some future studies are also pointed out.

2. DESIGN OF THE INTELLIGENT PREDICTIVE COTROLLER

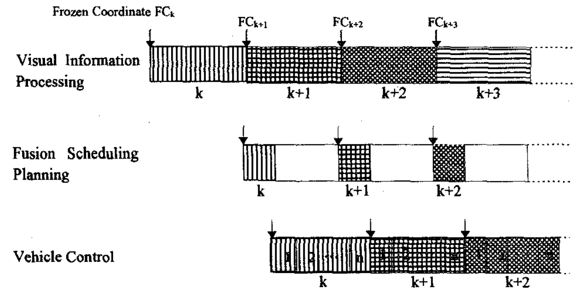
In this section, the characteristics of the robot vehicle are analyzed firstly. Then the intelligent predictive controller is designed.

Characteristics of the Vehicle

It has been shown that utilization of information related to the upcoming road characteristics and the vehicle model is an important factor in vehicle control. For example, when a driver is driving a vehicle, he has an internal model of the vehicle dynamics. Using this model, the driver can adjust the steering wheel angle according to noisy, delayed information which he perceives about road conditions. The view presented to the driver extends from a near-sight distance to a much greater far-sight distance. From this extensive visual field, the driver must extract the information necessary both to position the vehicle within the road lane, and to anticipate future course deviations. After being trained, most drivers can track a given path quite well.
The computer-controlled vehicle is similar to the driver-controlled one. In local planning-control mode, the assembly line and frozen coordinate system are often used so the local path is known before the control period.



(a). The frozen coordinate system of THMR-III



(b). The assembly line model of THMR-III

Fig. 1 The frozen coordinate system and assembly line

For example, the frozen coordinate system is used in the THMR-III system to describe the image processing, fusion, planning and control process in every cycle which is shown in Fig.1(a). Between instant T_k and instant T_{k+1}, frozen coordinate system FC_k is used, where the coordinate origin is the vehicle position at the image grabbing moment, the x-axis is the direction of the vehicle at that moment. Image processing, fusion, planning and control between T_k and T_{k+1} are all implemented at FC_k coordinate. After T_{k+1}, this procedure will be implemented at FC_{k+1} system. The procedures above are arranged as an assembly line, which is shown in Fig. 1(b).

Design the Intelligent Predictive Controller

According to the analysis of the characteristic of the vehicle, the intelligent predictive controller is designed. As shown in Fig.2, it comprises four principal components: a reference path, a predictive model, a set of online optimization algorithm and a feedback tuning model. The controller can first use a model of the vehicle to predict the future vehicle posture according to the current posture and the manipulating variables. Second it can calculate the future tracking error between the predictive posture and the planned ideal path created by the local path planning module. Then the online optimization algorithm can obtain the optimal

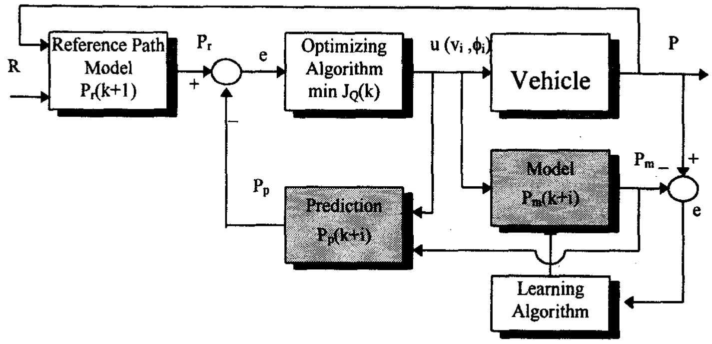


Fig.2 Schematic diagram of intelligent predictive control

manipulating variables in the next control period. The above process is updated and solved repeatedly.

3. COMPONENTS OF THE INTELLIGENT PREDICTIVE COTROLLER

The four principal components, i.e., the reference path model, the predictive model, the online optimization algorithm and feedback learning model, play an important role in the performance of the intelligent predictive controller. They are discussed in detail in this section.

The Reference Path Model

The reference path is the weighted average of the path planner output and the actual vehicle posture. In the future Q instants, it can be expressed as

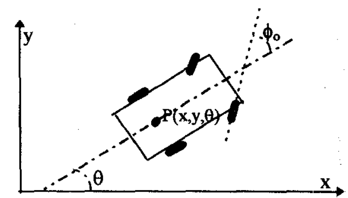
$$\boldsymbol{P_r(k)} = [P_r(k+1) \quad \cdots \quad P_r(k+Q)]^T \qquad (1)$$

where

$$P_r(k+i) = \alpha^i \cdot P(k)+(1-\alpha^i) \cdot R$$

The Vehicle Predictive Model

The predictive model is used to describe the reaction of the vehicle to control variables. Here we use steering model, speed model and posture model to represent the vehicle model, which is shown in Fig.3. The steering model describes the relationship between the steering angle command ϕ_i, the vehicle actual speed V_o and the actual steering angle ϕ_o , where the ϕ_i is the result of the path planning module. The speed model describes the relationship between the speed command V_i , the actual steering angle ϕ_o and the actual speed V_o , where the V_i is also the result of the path planning module. The posture model is used to represent the relationship between the actual vehicle speed V_o , the actual front wheel steering angle ϕ_o and the posture $P(x, y, \theta)$.



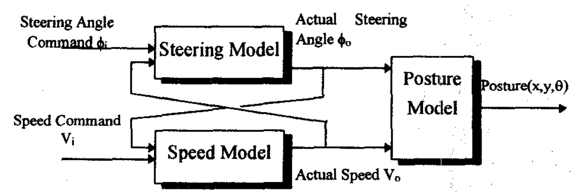


Fig.3 Schematic diagram of vehicle dynamic model

The steering model is the most important dynamic model of the vehicle which determines the characteristic of the obstacle avoidance and the path tracking. The difficulty of building the mathematical model of the system lies in: 1). The steering mechanism of the front wheels is nonlinear and 2) The lateral forces acting on the front wheels are related to many factors such as the vehicle speed, the material of the ground, the mass of the vehicle, etc.. It is shown that the neural networks have the ability to approximate large classes of nonlinear functions sufficiently accurately, which makes them the prime candidates for use in dynamic models for the representation of nonlinear process. In THMR-III, the forward model is used to represent the dynamics of the system. The model of the structure we used is shown in Fig.4.

The model of the neural network for identification can be represented as

$$\phi_o^m(k) = \hat{f}\,[\phi_o^P(k-1), \ \cdots, \phi_o^P(k-n); \ \phi_i(k-1), \ \cdots, \ \phi_i(k-)] \ (2)$$

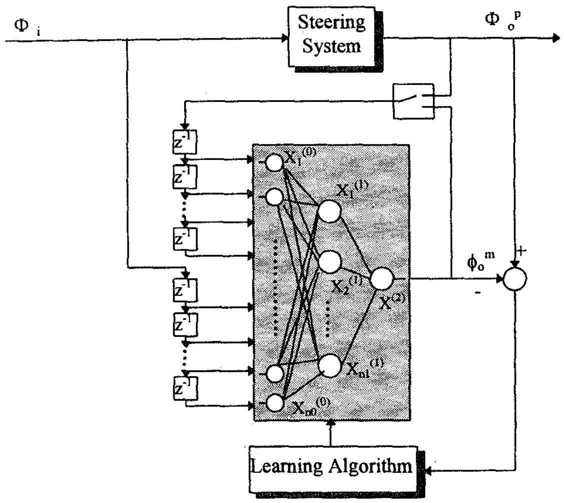


Fig.4 Structural of the neural network for THMR-III steering system identification

where

$\phi_o^m(k)$: the output of the network,

$\phi_o^P(k)$: the output of the system, i.e., the actual steering angle,

$\hat{f}$: the nonlinear input-output map of the network.

The result has shown that the model is suitable for identification of the steering system.

The speed model of THMR-III is much easier than the steering model, which can be approximately considered as a linear system. The traditional identification method is used to build the speed model.

The posture of the robot vehicle in the global coordinate system is denoted as $P(x, y, \theta)$, where (x,y) is the position of the vehicle and θ is the direction angle of the vehicle. In order to simplify the computation process and to improve the system reliability, the bicycle model is adopted here, which can be expressed as

$$\begin{cases} \theta(t) = \theta_o + \frac{1}{L}\int_0^t v(t)\cdot tg\phi(t)dt \\ x(t) = x_o + \int_0^t v(t)\cdot\cos\theta(t)dt \\ y(t) = y_o + \int_0^t v(t)\cdot\sin\theta(t)dt \end{cases} \tag{3}$$

The above steering model, speed model and posture model can be used to predict the posture $P(x, y, \theta)$ in the future Q instants. After $P(x, y, \theta)$ compared with (1), the future tracking error between the predictive posture and the reference path can be calculated, which is the base of optimization.

The Optimization Algorithm

The optimization algorithm is a rolling optimizing process. In every control step, the optimal object in the future Q instants is calculated as

$$\begin{aligned} \min\ J_Q(k) = &\sum_{i=1}^{Q} q_i\cdot[P_p(k+i)-P_r(k+i)]^2 + \\ &\sum_{j=1}^{M} w_j\cdot u^2(k+j-1) \end{aligned} \tag{5}$$

where

M is the time domain extent for optimization.

The posture in the optimal object can be represented as distance and angle, so (5) can be expressed further as

$$\begin{aligned} \min\ J_Q(k) = &\sum_{i=1}^{Q}[q_i\cdot d^2(k+i)+r_i\cdot\alpha^2(k+i)] + \\ &\sum_{j=1}^{M} w_j\cdot u^2(k+j-1) \end{aligned} \tag{6}$$

where

d is the distance between the reference model and the predictive path and α is the posture angle difference between the reference model and the predictive path, i.e.

$$\begin{aligned} d(i) &= \sqrt{(x_r(i)-x_p(i))^2+(y_r(i)-y_p(i))^2} \\ \alpha(i) &= \theta_r(i)-\theta_p(i) \end{aligned} \tag{7}$$

The optimizing problem (6) is solved by a dynamic planning algorithm.

The Feedback Tuning Model

Because there exists error between the predictive model and the practical vehicle, the feedback tuning model must be used to correct the error. In Fig.2, The on-line learning algorithm is adopted to learn and adjust the predictive model (2) in real time. However, it will cost a lot of time due to the computational complexity. In fact, the learning algorithm is only activated at the end of every planning cycle. In every control cycle, the following equation is used to tune the predictive model

$$\begin{bmatrix} P_p(k+1) \\ P_p(k+2) \\ \vdots \\ P_p(k+Q) \end{bmatrix} = \begin{bmatrix} P_m(k+1) \\ P_m(k+2) \\ \vdots \\ P_m(k+Q) \end{bmatrix} + \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_Q \end{bmatrix}\cdot e(k) \tag{8}$$

Finally, we can summarize the intelligent predictive control algorithm as follows

(1) *Read the path from the planning module and calculate the reference path model with (1);*

(2) *According to $\phi_o^P(k)$, $\phi_o^P(k-1)$, $\cdots$, $\phi_o^P(k-n+1)$; $\phi_i(k)$, $\phi_i(k-1)$, $\cdots$, $\phi_i(k-m+1)$ and the neural network model, calculate the predictive steering angle in the next*

Q instants: $\phi_o^m(k+1), \phi_o^m(k+2), \cdots, \phi_o^m(k+Q)$;

(3) *Calculate the predictive speed in the next Q instants:* $V_o^m(k+1), V_o^m(k+2), \cdots, V_o^m(k+Q)$;

(4) *According to (3), calculate*

$$P_m(k)=\begin{bmatrix}\theta_m(k+1) & \theta_m(k+2) & \cdots & \theta_m(k+Q)\\ x_m(k+1) & x_m(k+2) & \cdots & x_m(k+Q)\\ y_m(k+1) & y_m(k+2) & \cdots & y_m(k+Q)\end{bmatrix};$$

(5) *Calculate the distance error and posture angle error with (7);*

(6) *According to the optimal object (6), calculate the optimal control variable in the next Q instants:*

$$u_p(k)=\begin{bmatrix}v_i(k) & v_i(k+1) & \cdots & v_i(k+Q-1)\\ \phi_i(k) & \phi_i(k+1) & \cdots & \phi_i(k+Q-1)\end{bmatrix};$$

(7) *Output* $u(k)=(v_i(k), \phi_i(k))^T$ *to the implementation module;*

(8) $k \leftarrow k+1$;

(9) *if* (*k< control cycle times*)
then
tune the predictive model with (8);
goto step (2);
else
learn the predictive model online;

(10) *return;*

4. RESULT OF APPLICATION

The intelligent predictive control strategy has been successfully applied to our outdoor four-wheel mobile robot THMR-III. The result is shown in Fig.5. One curve in this figure is the planned ideal path, the other is the actual trace of THMR-III controlled by the intelligent predictive controller. From the result we can see that the features of the controller such as tracking time, overshoot and are quite satisfactory. The most remarkable superiority of the method is its robustness. Even when the driving conditions vary, the intelligent predictive controller can still remain stable and can control the vehicle to follow the given path. The test result illustrated in Fig.6 shows this feature. The map displays the global environment of the square in front of the main building at Tsinghua University. The planned global path is a closed path and its shape is like an Arabic numeral 8, i.e., A-B-C-D-B-C-A. The path from A to B is a curved road. Near Point B there is a branch road. From B to C there is a white line. The path from C to D is a straight road. There is a branch road near point D. The path from D to B is like that from A to B. The path from C to A is also a straight road. Point A is both the original and goal point. The trace of THMR-III is also illustrated in this figure. From the result, we can see that the intelligent predictive controller is reliable and robust.

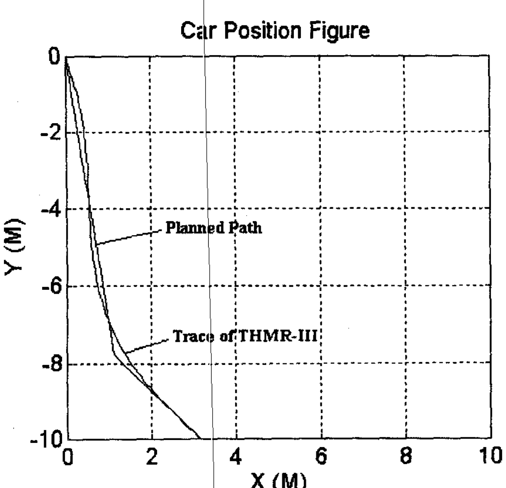


Fig. 5 The planned path and the actual trace of THMR-III controlled by the intelligent predictive controller

5. CONCLUSION

An intelligent predictive control approach to the path tracking problem of autonomous mobile robot is presented in this paper based on the analysis of the characteristics of the vehicle model and the traditional predictive control algorithm. The intelligent predictive controller can first use a neural network model of the vehicle to predict future vehicle posture according to the current posture and manipulating variables. It can calculate the future tracking error between the predicted posture and the planned ideal path. Then the online

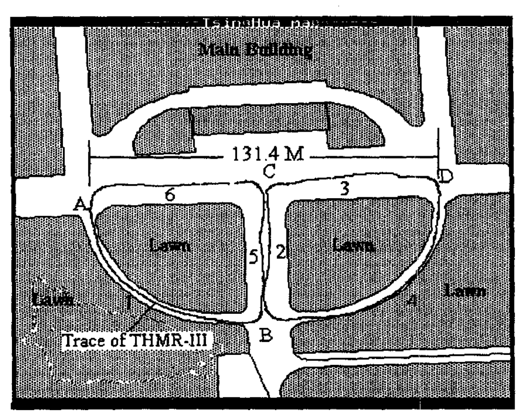


Fig. 6 The trace of THMR-III navigated by the local behavior control method

optimization algorithm can compute the optimal manipulating variables in the next control period. The above process is updated and solved repeatedly. The result of application shows that the features of the whole system such as tracking time, overshoot and robustness are quite satisfactory. The THMR-III, which is an outdoor autonomous mobile robot controlled by this controller, can run in the square in front of the main building on our campus. The max speed is 15km/h.

Our immediately future work is to apply this method to our new generation of Autonomous Mobile Robot—THMR-V.

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