Journal of Computational Science & Engineering 17 (2015) 593-596

Available at http://www.asocse.org ISSN 1710-4068

Predictive control method study for intelligent vehicle based on the data driven control

Li Yang, Lili Bai*, Huizhen Zhang

Department of Electrical Information Engineering, Northeast Petroleum University, Daqing, 16300, China

Abstract: **During the control process of intelligent vehicle, various factors like change in load and vehicle abrasion will make it difficult to accurately establish vehicle steering system and driving system model. Based on data driven control algorithm, the paper made direct use of measured speed as well as steering engine angle, directly identified controller parameter, avoided model identification process, and directly designed controller based on a certain optimized performance index to improve controlling accuracy. Simulation results showed that the method featured outstanding controlling performance.**

Keywords: Data driven; Intelligent vehicle; System identification; Predictive control

Received 20 January 2015, Revised 26 March 2015, Accepted 28 March 2015

* Corresponding Author: Lili Bai, zy@qq.com

1. Introduction

Intelligent vehicle is a typical strongly non-linear system with nonholonomic constraint. The coupling between the vehicle's steering control system and drive control system affects the system of multi-input and multi-output. To ensure the intelligent vehicle moves according to predefined track, the steering engine and running speed of the vehicle must be controlled timely. In order to ensure the vehicle has sensitive control, the mathematic model of the steering system must be obtained. High order model can fully reflect true properties of the actual system, but it is easily affected by noise. Especially under the situation that the steering system has uncertain parameters and there exists external disturbance, such as load change, abrasion of the intelligent vehicle, and unstable supply voltage. Method based on mechanism analysis cannot reflect characteristics of the system.

In document [1], a controller is designed based on receding horizon. The kinetic control system of the intelligent vehicle is handled as a rigid body, and the influence of factors of external disturbance and uncertainty of parameters is not considered. In document [2], the steering system model and drive system model of the intelligent vehicle are obtained with system identification method; and in the design of the controller, the kinetic control system is taken as a multi-input and multi-output system. In document [3], a parameter experimental identification method based on longitudinal kinetic model of the vehicle is brought up, and it identifies kinetic parameters of vehicle based on the least square method. In document [4], an adapting cruise control system designed based on fuzzy logic and synovial control theory is brought up, which enables vehicles to accurately track the expected acceleration. In all the above documents, the kinetic control system model gets identified first, and then the controller is designed based the model, which increases complexity of the algorithm. In the process of practical control, the operation system model and driving system model will change with the speed, and therefore the effect of control based on model design shall be further improved [5].

In this article, the control algorithm is driven by data based sub-space identification, the controller parameters are directly identified with the offline and online information as well as the prediction information, and the model identification process is avoided. The optimization based some performance index designs controller for the drive system and steering system respectively, so as to get good control effect.

2. Problem Description

The kinematical equation for the wheeled mobile robot is:

$$\begin{cases} \dot{x} = v\cos\theta \\ \dot{y} = v\sin\theta \\ \dot{\theta} = \omega \end{cases} \quad (1)$$

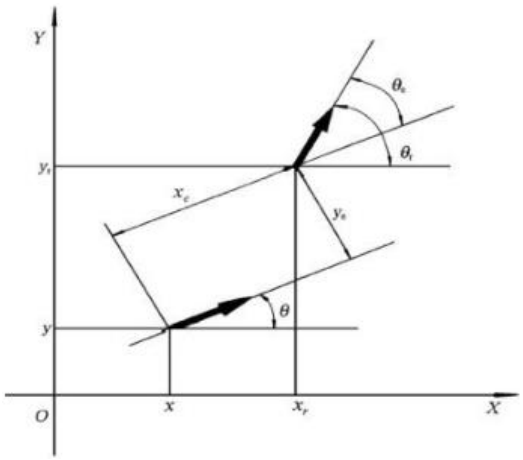

Figure 1. Coordinates representation of pose error

2015 © The American Computational Science Society. All rights reserved.

In the above equation, (x, y) is the position of the mobile robot; θ is its direction angle, i.e. the included angle between heading and x axis; v and ω are linear speed and angular speed of the mobile robot, and in kinematics model, they are control input. The track tracking considered in this article is the tracking of mobile robot to the reference vehicle with position (x_r, y_r, θ_r) and speed v_r, ω_r. As shown in Figure 1.

Hence we can get the position error described within the coordinates of mobile robot:

$$\begin{bmatrix} x_e \\ y_e \\ \theta_e \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_r - x \\ y_r - y \\ \theta_r - \theta \end{bmatrix} \quad (2)$$

And the differential equation for position error is described as:

$$\begin{aligned} \dot{x}_e &= \omega y_e - v + v_r \cos\theta_e \\ \dot{y}_e &= -\omega x_e + v_r \sin\theta_e \\ \dot{\theta}_e &= \omega_r - \omega \end{aligned} \quad (3)$$

In this paper, smart car objectively controlled with rear-wheel driving and front wheel steering was studied. From formulas (2) and (3), it is seen that the velocity V and angular velocity of smart car should be simultaneously controlled to ensure that it runs following the intended path. That is, the motion system of smart car is a multi-input and multi-output control system, and its movements in three-dimensional configuration space were realized by controlling using driving inputs and steering inputs. In this paper, based on the data driven control principle and the online, offline and predicted information, the controller for driving control system and steering control system was directly designed.

3. Controller Design

Consider the following discrete state space model [6]:

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) + \boldsymbol{K}\boldsymbol{v}(k) \quad (4)$$

$$\boldsymbol{y}(k) = \boldsymbol{C}\boldsymbol{x}(k) + \boldsymbol{D}\boldsymbol{u}(k) + \boldsymbol{v}(k) \quad (5)$$

Among them, $\boldsymbol{u}(k)$, $\boldsymbol{y}(k)$ and $\boldsymbol{x}(k)$ respectively is the system input, output and quantity of state. A,B,C,D and K are matrices with proper dimension. Assuming (A, B) is controllable and (A, C) is observable. If not given the effect of noise, according to the formula (4) and (5), we can get the following equation;

$$\boldsymbol{Y}_{\mathrm{f}} = \boldsymbol{\Gamma}\boldsymbol{X}_{\mathrm{f}} + \boldsymbol{H}_{\mathrm{f}}\boldsymbol{U}_{\mathrm{f}}$$

Or

$$\boldsymbol{Y}_{\mathrm{p}} = \boldsymbol{\Gamma}\boldsymbol{X}_{\mathrm{p}} + \boldsymbol{H}\boldsymbol{U}_{\mathrm{p}} \quad (6)$$

Then the subspace model identification problem proceed from input measure value $\boldsymbol{u}(k)$ and output measure value $\boldsymbol{y}(k)$, where $k \in \{0,1,\cdots,2N+j-2\}$, First of all, we have constructed Hankel matrix of N rows and j columns.

$$\boldsymbol{U}_{\mathrm{p}} = \begin{pmatrix} \boldsymbol{u}(1) & \boldsymbol{u}(2) & \cdots & \boldsymbol{u}(j) \\ \boldsymbol{u}(2) & \boldsymbol{u}(3) & & \boldsymbol{u}(j+1) \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{u}(N-1) & \boldsymbol{u}(N) & \cdots & \boldsymbol{u}(N+j-1) \end{pmatrix},$$

$$\boldsymbol{U}_{\mathrm{f}} = \begin{pmatrix} \boldsymbol{u}(N) & \boldsymbol{u}(N+1) & \cdots & \boldsymbol{u}(N+j) \\ \boldsymbol{u}(N+1) & \boldsymbol{u}(N+2) & & \boldsymbol{u}(N+j+1) \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{u}(2N-1) & \boldsymbol{u}(2N) & \cdots & \boldsymbol{u}(2N+j-1) \end{pmatrix}$$

Among them, the subscript p and f, respectively express past and future. Y_f and Y_p are defined in the same manner. $\boldsymbol{X}_{\mathrm{f}} = \begin{bmatrix} \boldsymbol{x}_N & \boldsymbol{x}_{N+1} & \cdots & \boldsymbol{x}_{N+j-1} \end{bmatrix}^{\mathrm{T}}$ is state sequence.

$$\boldsymbol{H} = \begin{bmatrix} \boldsymbol{CB} & \boldsymbol{0} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{CAB} & \boldsymbol{CB} & \boldsymbol{0} & \boldsymbol{0} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{CA}^{N-1}\boldsymbol{B} & \boldsymbol{CA}^{N-2}\boldsymbol{B} & & \boldsymbol{CB} \end{bmatrix},$$

$$\boldsymbol{\Gamma} = \begin{bmatrix} \boldsymbol{C} \\ \boldsymbol{CA} \\ \vdots \\ \boldsymbol{CA}^{N-1} \end{bmatrix}, \quad \boldsymbol{W}_{\mathrm{p}} = \begin{bmatrix} \boldsymbol{U}_{\mathrm{p}} \\ \boldsymbol{Y}_{\mathrm{p}} \end{bmatrix}$$

Then the subspace model identification problem can be described as the following: providing the past input W_p and output as well as the future input U_f, the optimal predictive value of future output was searched, that is:

$$\hat{\boldsymbol{Y}}_{\mathrm{f}} = \boldsymbol{L}_w\boldsymbol{W}_{\mathrm{p}} + \boldsymbol{L}_u\boldsymbol{U}_{\mathrm{f}} \quad (7)$$

Wherein, L_W and L_u are subspace state matrix and input matrix. It can be obtained by the least squares problem:

$$\min \left\| \boldsymbol{Y}_{\mathrm{f}} - (\boldsymbol{L}_w, \boldsymbol{L}_u) \begin{pmatrix} \boldsymbol{W}_{\mathrm{p}} \\ \boldsymbol{U}_{\mathrm{f}} \end{pmatrix} \right\|_F^2 \quad (8)$$

Subspace identification solves the above least squares problem by using linear algebra tools QR decomposition and SVD decomposition. The optimal predicted value $\hat{Y}_f$ of future output Y_f can be described as the orthogonal mapping from column space Y_f to the column subspace spanned by W_p

2015 © The American Computational Science Society. All rights reserved.

and U_f.

$$\hat{\boldsymbol{Y}}_{\mathrm{f}} = \boldsymbol{Y}_{\mathrm{f}} / \begin{pmatrix} \boldsymbol{W}_{\mathrm{p}} \\ \boldsymbol{U}_{\mathrm{f}} \end{pmatrix} = \boldsymbol{L}_w \boldsymbol{W}_{\mathrm{p}} + \boldsymbol{L}_u \boldsymbol{U}_{\mathrm{f}} \tag{9}$$

Solutions of the problem are orthogonal mapping from column space Y_f to W_p and U_f, numerical implementation of the mapping can be obtained by the decomposition of RQ.

$$\begin{bmatrix} \boldsymbol{W}_{\mathrm{p}} \\ \boldsymbol{U}_{\mathrm{f}} \\ \boldsymbol{Y}_{\mathrm{f}} \end{bmatrix} = \boldsymbol{R}\boldsymbol{Q} = \begin{bmatrix} \boldsymbol{R}_{11} & \boldsymbol{0} & \boldsymbol{0} \\ \boldsymbol{R}_{21} & \boldsymbol{R}_{22} & \boldsymbol{0} \\ \boldsymbol{R}_{31} & \boldsymbol{R}_{32} & \boldsymbol{R}_{33} \end{bmatrix} \begin{bmatrix} \boldsymbol{Q}_1^{\mathrm{T}} \\ \boldsymbol{Q}_2^{\mathrm{T}} \\ \boldsymbol{Q}_3^{\mathrm{T}} \end{bmatrix} \tag{10}$$

$$\boldsymbol{L} = \begin{bmatrix} \boldsymbol{L}_w & \boldsymbol{L}_u \end{bmatrix} = \begin{bmatrix} \boldsymbol{R}_{31} & \boldsymbol{R}_{32} \end{bmatrix} \begin{bmatrix} \boldsymbol{R}_{11} & 0 \\ \boldsymbol{R}_{21} & \boldsymbol{R}_{22} \end{bmatrix}^{\dagger} \tag{11}$$

Where " † "represents Moore-Penrose pseudo-inverse, pseudo-inverse matrix can be solved by decomposition SVD.

The adaptive control strategy is adopted in the thesis, at time $k-1$, future output can be estimated according to the future output, data $u_p = [u_{k-N}, \cdots, u_{k-1}]$ and $y_p = [y_{k-N}, \cdots, y_{k-1}]$ has measured. Updating the system parameter according to the new input and outputting data at the next sampling time.

$$\hat{\boldsymbol{y}}_{\mathrm{f}} = \boldsymbol{L}_w \boldsymbol{w}_{\mathrm{p}} + \boldsymbol{L}_u \boldsymbol{u}_{\mathrm{f}} \tag{12}$$

The paper uses the quadratic performance index as follows:

$$J = \sum_{i=1}^{H_p} (\boldsymbol{r}(k+i) - \hat{\boldsymbol{y}}(k+i))^{\mathrm{T}} \boldsymbol{Q} (\boldsymbol{r}(k+i) - \hat{\boldsymbol{y}}(k+i)) + \sum_{i=0}^{H_c-1} \boldsymbol{u}(k+i)^{\mathrm{T}} \boldsymbol{R}\boldsymbol{u}(k+i) = (\boldsymbol{r} - \hat{\boldsymbol{y}}_{\mathrm{f}})^{\mathrm{T}} \boldsymbol{Q} (\boldsymbol{r} - \hat{\boldsymbol{y}}_{\mathrm{f}}) + \boldsymbol{u}_{\mathrm{f}}^{\mathrm{T}} \boldsymbol{R}\boldsymbol{u}_{\mathrm{f}} \tag{13}$$

Where H_p and H_c are predictive domain and control domain, $Q = diag(Q_1 \cdots Q_{H_c}) > 0$ is positive symmetric matrix, $R = diag(R_1 \cdots R_{H_c}) \geq 0$ semi positive definite symmetric matrix, r is the reference input sequence, solving the upper bound of performance measures , let $\frac{\partial J}{\partial \boldsymbol{u}_{\mathrm{f}}} = 0$, we can get:

$$\boldsymbol{u}(k) = (\boldsymbol{R} + \boldsymbol{L}_u^{\mathrm{T}} \boldsymbol{Q} \boldsymbol{L}_u)^{-1} \boldsymbol{L}_u^{\mathrm{T}} \boldsymbol{Q} (\boldsymbol{r} - \boldsymbol{L}_w \boldsymbol{W}_{\mathrm{p}}) \tag{14}$$

Only the first control law is applied to practical system.

$$\boldsymbol{u}(k) = (\boldsymbol{I} \quad 0 \quad \cdots \quad 0)(\boldsymbol{R} + \boldsymbol{L}_u^{\mathrm{T}} \boldsymbol{Q} \boldsymbol{L}_u)^{-1} \boldsymbol{L}_u^{\mathrm{T}} \boldsymbol{Q} (\boldsymbol{r} - \boldsymbol{L}_w \boldsymbol{W}_{\mathrm{p}}) \tag{15}$$

4. Simulation Analysis

According to the description of the literature [2], the steering system model is:

$$G(s) = \frac{0.04052}{s^2 + 16.44s + 399.04}$$

The driving system model is:

$$G(s) = \frac{0.002}{s^2 + 2.145s + 1.718}$$

The stepping motor rotated a certain angle and moved a step ahead via every electrical pulse input, whose angular displacement output was proportional to the number of electrical pulse input. Electrical pulse signals with amplitudes of 1 and 0.2 were given to steering control system and driving control system respectively as disturbance inputs, which were shown as the dashed lines in figure 2 and figure 3. The responsive outputs of driving control system of rotator and steering system of servo were shown in figure 2 and figure 3.

In which the solid lines were the increment of angular velocity and velocity. The simulation results showed that the data based driving prediction control algorithm still can achieve a good output result even with external disturbance input.

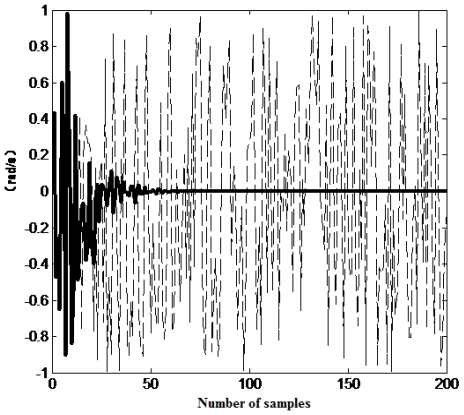

Figure 2. Output curve of motor driving control system

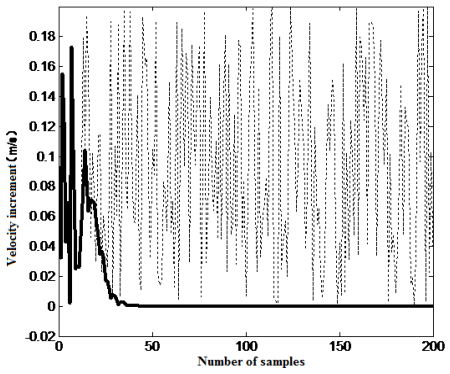

Figure 3. Output curve of steering control system

2015 © The American Computational Science Society. All rights reserved.

5. Conclusions

The system of driving control and steering control of smart car is a typical multi-input and multi-output system with strong coupling, in this paper, this multi-input and multi-output system was divided into two sub-systems for designing controllers respectively. Based on the predictive control theory, the parameters of controllers were identified by directly using offline, online and predicted information, with data-driven controllers designed by avoiding the model identification process. In this paper, based on subspace method, the parameters of controllers were online identified, and relative good control effects were achieved under conditions including system aging, tire wearing or battery voltage instability, with relative strong environmental adaptability possessed.

Acknowledgment

This work has been jointly supported by the School Research Funds of Northeast Petroleum University (NEPUQN2014-04) and Science and Technology Research Project of Heilongjiang Province Education Department (12531062).

References

[1] D.B. Gu, H.S, IEEE Transcations on Systems Technology, 4 (2006) 743-749.
[2] F. You, R.B. Wang, China Journal of Highway and Transport, 21 (2006) 111-117.
[3] J.X. Liu, S.B. Li, J.Q. Wang, Transactions of the Chinese Society for Agricultural Machinery, 10 (2010) 5-10.
[4] Y.N. Li, J. Ji, L. Zheng, S.E. Zhao, China Mechanical Engineer, 11 (2010) 1374-1381.
[5] L. Pacheco, N.S. Luo, International Journal of Innovation Computing Information and Control, 6 (2011) 3457-3483.
[6] H. Yang, S.Y. Li, Control Theory and Applications, 5 (2007) 732-736.

2015 © The American Computational Science Society. All rights reserved.