Neuro-Adaptive Control of High-Speed Trains under Uncertain Wheel-Rail Relationship

Zhechen Wang*
The Seventh Research Division and the Center for Information and Control,
School of Automation Science and Electrical Engineering,
Beihang University (BUAA), Beijing 100191, P.~R.~China

Yingmin Jia
The Seventh Research Division and the Center for Information and Control,
School of Automation Science and Electrical Engineering,
Beihang University (BUAA), Beijing 100191, P.~R.~China
E-mail: yipin_yipin@163.com, ymjia@buaa.edu.cn

Abstract

Traditional automatic controller designing in train systems is almost based on urban rail transit where the influence of changing wheel-rail relationship caused by the variation of speed and environment is ignored. However, high-speed railway operates in more open environment and higher speed, which leading to a more complex variation of wheel-rail relationship occurring. In this paper, we design an automatic train controller in high-speed railway which can realize the automatic velocity tracking even if the uncertain and nonlinear variation of complex wheel-rail relationship happens. First of all, the train dynamic model is established where the wheel-rail relationship is expressed as an uncertain unknown function and the train operation system is expressed as a third-order nonlinear system. Then, a neural network adaptive controller is designed by using the backstepping method and barrier Lyapunov function. Based on this controller, position and velocity tracking errors are semi-globally uniformly ultimate boundedness. Finally, the effectiveness of the algorithm is verified by simulation experiments.

Keywords: Train velocity tracking, adaptive control, wheel-rail relationship, barrier Lyapunov function.

1. Introduction

Unmanned operation has been attempted successfully in urban mass transit. However, it fails in high-speed railway due to higher speed, wider range and more complex environmental changes. Precisely position and velocity tracking is one of the crucial task for high-speed railway. Thus, considerable research focuses on automatic operation or cruise control.

In the last decade, research in the field of cruise control could be categorized into three groups, PID control, robust adaptive control and intelligent control.[1] Typical PID control was the most widely used methods in train control system in early years.[2] Nevertheless, frequent switches of control law and appropriate parameter chosen are two issues that are not able to overcome. Intelligent approaches such as expert systems and reinforcement learning help improve the performance of safety, energy efficiency, comfort and punctuality as shown in Refs. 3-4. Robust adaptive approaches are generally model-based. As the problems of fault tolerant in Ref. 5, actuation notches in Ref. 6, antiskid constraints, input saturation in Refs.7-8, communication delays in Ref. 9 were considered about, train model got closer to the reality. In terms of the control methods, H∞ control in Ref. 10, terminal sliding mode control in Ref. 11 were used in research.

Although lots of research results have been achieved in the field of cruise control, the influence of complex relationship between wheels and rail on train control have not been considered. On the one hand, the wheel-rail model is difficult to describe by an accurate dynamic model. On the other hand, the adhesion coefficient changes drastically in different weather condition. These characteristics cause the increasing difficulty of controller designing. Some research studied the optimal adhesion control problem which means to find a controller to keep the wheel-real relationship in the best state which can be found in Refs 12-15. Different from optimal adhesion control, we are supposed to achieve the cruise control by taking advantage of the idea of active adhesion control. The train dynamics equation combined with the wheel dynamic equation formulate the system dynamics, which can express not only the relationship between rail and wheels but also the effect of the environmental changes on train dynamic system.

2. Problem Formulation

The multi-point motion model and wheel dynamic model of a high-speed train are as follows.

$$\dot{p}_i = v_i, \quad (1)$$

$$m_i \dot{v}_i = \mu_i m_i g + f_{i+1,i} - f_{i,i-1} - f_{ri}, \quad (2)$$

$$j_i \dot{\omega}_i = T_i - \mu_i m_i g r_i, \quad (3)$$

where p , v , ω , T are train position, train velocity, angular velocity of wheels and the traction torque respectively. m , j , r and g are mass, wheel inertia, wheel radius and gravity constant respectively. The subscript i represents the ith carriage of the train. $f_{i+1,i}$ represents the coupler force between the (i+1)th and the ith carriage, which can be expressed as

$$f_{i+1,i} = k_{i+1,i} \cdot \left(p_{i+1} - p_i - l_{i+1,i}\right) + \delta\left(p_{i+1} - p_i - l_{i+1,i}\right), i = 2, \ldots, n-1.$$

$$f_{n+1,n} = f_{1,0} = 0, \quad (4)$$

where $k_{i+1,i}$ is the stiffness and f_{ri} describes the resistance force of a carriage by Davis formula,

$$f_{ri} = a_i + b_i v_i + c_i v_i^2, \quad (5)$$

where a , b and c are unknown positive constants with known upper bound. Adhesion coefficient μ which depends on plenty of factors, such as temperature, humidity, surface roughness, surface cleanliness, etc,[3] illustrates the complex wheel-rail system. According to previous research[13], μ can be described by a uncertain function related to the slip ratio given as

$$\lambda_i = \frac{\omega_i v_i - v_i}{v_i}. \quad (6)$$

From fig.2, it is obvious that μ is an unimodal function in the first and the third quadrant respectively. Additionally, $d\mu/d\lambda > 0$ is satisfied in the stable region $\Omega := \left\{(\lambda,\mu)\middle| -\lambda_{\max} < \lambda < \lambda_{\max}\right\}$.

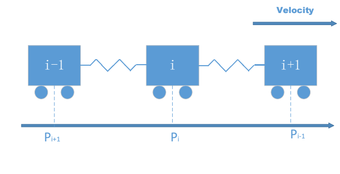

Fig.1. Train model

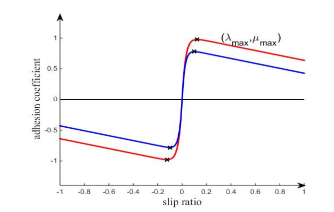

Fig. 2. The wheel-rail relationship

Based on the train model and wheel model, the object of this paper is to find a controller which is able to realize the following goals.

1. To force the velocity and position track a desired trajectory, i.e. $x_i(t) \to x_{id}(t)$, $v_i(t) \to v_{id}(t)$.
2. To ensure the coupler force in a safe range, i.e. $\left|f_{i+1,i}\right| \le f_{c,\max}, \forall t > 0, i = 2, \ldots, n-1$.
3. To ensure train anti-slip operation i.e. $|\mu| \le \mu_{\max}, \forall t > 0$.

It is easy to find that the problem we are talking about is a tracking problem for nonlinear and uncertain system with constrained output.

To this end, the following definitions, assumptions and lemma are imposed on system (1)-(3).

Define 1

$$x_i = p_i - \sum_{k=1}^{i} l_{k+1,k} \quad (7)$$

Assumption 1

Slip ratio is in stable area when train moves, i.e.

$$\theta = \frac{d\mu}{d\lambda} \ge \underline{\theta} > 0, \forall t > 0.$$

Assumption 2

The position, velocity and adhesion coefficient of a train is measureable.

Lemma 1[16] *If there exists a* C^1 *continuous and positive definite Lyapunov function* $V(x)$ *satisfying* $\kappa_1(\|x\|) \le V(x) \le \kappa_2(\|x\|)$ *with bounded initial*

conditions, such that $\dot{V}(x) \le -\rho V(x) + c$,
where $\kappa_1, \kappa_2 : \mathbb{R}^n \to \mathbb{R}$ *are class* ***K*** *functions,*
and ρ, c *are two positive constants, then the solution* $x(t)$ *is uniformly bounded.*

Take (7) into (1), we obtain that

$$\dot{x}_i = \dot{p}_i \tag{8}$$

In order to separate the uncertain parts from the system, (2) can be rewritten as

$$\dot{v} = \mu_i g + f_{i1} + \Delta f_{i1}, \tag{9}$$

where

$$f_{i1} = \frac{1}{m_i}\left[\hat{k}_{i+1,i}\left(x_{i+1} - x_i\right) - \hat{k}_{i,i-1}\left(x_i - x_{i-1}\right) - \left(\hat{a}_i + \hat{b}_i v_i + \hat{c}_i v_i^2\right)\right]$$

presents the certain part, $\Delta f_{i1} = \Delta f_{i1}\left(x_{i+1} - x_i, x_i - x_{i-1}, v_i\right)$ is the uncertain part, $\hat{k}_{i+1,i}, \hat{k}_{i,i-1}, \hat{a}_i, \hat{b}_i, \hat{c}_i$ are the estimated parameters obtained by experience and is closely near the real value. Similarly, through (2),(6) and (7), (3) is transformed as

$$\dot{\mu}_i = \theta_i\left[\frac{r_i}{j_i v_i}T_i - \left(\frac{m_i r_i^2}{j_i v_i} + \frac{\lambda_i + 1}{v_i}\right)g\mu_i - \frac{\left(\lambda_i + 1\right)\left(f_{i+1,i} - f_{i,i-1} - f_{ri}\right)}{m_i v_i}\right], \tag{10}$$

where $\theta_i = \frac{d\mu_i}{d\lambda_i}$, $f_{i2} = -\left(\frac{m_i r_i^2}{j_i v_i} + \frac{\lambda_i + 1}{v_i}\right)g\mu_i - \frac{\left(\lambda_i + 1\right)f_{i1}}{v_i}$ is the certain part, $\Delta f_{i2} = \Delta f_{i2}\left(\lambda, x_{i+1} - x_i, x_i - x_{i-1}, v_i\right)$ is the uncertain part.

For the sake of estimating the uncertain terms, neural networks is proved as an appropriate method. From Ref. 17, we know that for any given continuous function $f(X): R^m \to R$ and an arbitrary $\delta > 0$, there exists a neural network $W^{*T}h(X)$, such that $\left|f(X) - W^{*T}h(X)\right| \le \delta$, where

$$W^* := \arg\min_{W}\left\{\sup_{X}\left|f(X) - W^T h(X)\right|\right\} \tag{11}$$

is the optimal weight vector,

$$h(X) = \left[h_1(X), h_2(X), \ldots, h_l(X)\right]^T \tag{12}$$

is the Gaussian basis function vector which can be expressed as

$$h_i(X) = \exp\left(-\frac{\left\|X - c_i\right\|^2}{\sigma_i^2}\right), i = 1, 2, \ldots, l \tag{13}$$

In general, W^* and are bounded by the constants .
According to the NN estimation, system(8)(9)(10) can be detailed as

$$\begin{aligned} \dot{x}_i &= v_i \\ \dot{v}_i &= g\mu_i + f_{i1} + W_{i1}^{*T}h_{i1}(\cdot) + \varepsilon_{i1}(\cdot) \\ \dot{\mu}_i &= \theta_i\left(\frac{r_i}{j_i v_i}T + f_{i2}\right) + W_{i2}^{*T}h_{i2}(\cdot) + \varepsilon_{i2}(\cdot) \end{aligned} \tag{14}$$

Then the control problem becomes to a stability problem for system (14) with state constraints.

3. Controller Design and Stability Analysis

In this section, the backstepping procedure is employed to design a neuro-adaptive controller.

Denote that

$z_{i1} = x_i - x_{id}$, $z_{i2} = v_i - v_{id} - \alpha_{i1}$, $z_{i3} = \mu_i - \alpha_{i2}$.

Give the Lyapunov and barrier Lyapunov function candidate,

$$V_{i1} = \frac{1}{2}\ln\frac{z_{i1m}^2}{z_{i1m}^2 - z_{i1}^2}, \tag{15}$$

$$V_{i2} = \frac{1}{2}z_{i2}^2 + \frac{1}{2}\tilde{\varphi}_{i1}^2, \tag{16}$$

$$V_{i3} = \int_0^{z_{i3}} \frac{\tau\mu_{im}^2}{\mu_{im}^2 - \left(\tau + \alpha_{i2}\right)^2}d\tau + \frac{1}{2}\tilde{\varphi}_{i2}^2, \tag{17}$$

$$V_i = V_{i1} + V_{i2} + V_{i3} \tag{18}$$

where $\tilde{\varphi}_{ij} = \varphi_{ij} - \hat{\varphi}_{ij}, j = 1, 2,$ $\hat{\varphi}_{ij}$ is the estimation of φ_{ij} which is an adaptive parameter of NN weight vector to reduce the online computer burden.

Step 1.

Take derivative of (15), we have

$$\dot{V}_{i1} = \frac{z_{i1}z_{i2}}{z_{i1m}^2 - z_{i1}^2} + \frac{z_{i1}\alpha_{i1}}{z_{i1m}^2 - z_{i1}^2}. \tag{19}$$

Design the virtual control law as

$$\alpha_{i1} = -k_{i1}z_{i1}, \tag{20}$$

then

$$\dot{V}_{i1} = -\frac{k_{i1}z_{i1}^2}{z_{i1m}^2 - z_{i1}^2} + \frac{z_{i1}z_{i2}}{z_{i1m}^2 - z_{i1}^2}. \tag{21}$$

Step 2.

The derivative of (16) is

$$\begin{aligned} \dot{V}_{i2} &= z_{i2}\dot{z}_{i2} + \tilde{\varphi}_{i1}\dot{\tilde{\varphi}}_{i1} \\ &= gz_{i2}z_{i3} + z_{i2}\left(W_{i1}^{*T}h_{i1} + \varepsilon_{i1}\right) - \frac{z_{i1}z_{i2}}{z_{i1m}^2 - z_{i1}^2} \\ &\quad + z_{i2}\left(g\alpha_{i2} + f_{i1} - \dot{v}_{id} - \dot{\alpha}_{i1} + \frac{z_{i1}}{z_{i1m}^2 - z_{i1}^2}\right). \end{aligned} \tag{22}$$

From Young's inequality, we get

$$z_{i2}W_{i1}^{*T}h_{i1} \le \frac{z_{i2}^2\varphi_{i1}^2}{2a_{i1}^2}h_{i1}^T h_{i1} + \frac{a_{i1}^2}{2}, \tag{23}$$

$$z_{i2}\varepsilon_{i1} \le \frac{z_{i2}^2}{2b_{i1}^2} + \frac{b_{i1}^2\varepsilon_{i1m}^2}{2}. \tag{24}$$

Design the virtual control law as

$$\alpha_{i2} = \frac{1}{g}\Big(-k_{i2}z_{i2} - f_{i1} + \dot{v}_{id} + \dot{\alpha}_{i1} - \frac{z_{i2}}{z_{i1m}^2 - z_{i1}^2} - \frac{z_{i2}\hat{\varphi}_{i1}}{2a_{i1}^2}h_{i1}^T h_{i1} - \frac{z_{i2}}{2b_{i1}^2}\Big), \tag{25}$$

With the adaptive law

$$\dot{\hat{\varphi}}_{i1} = \frac{z_{i2}^2}{2a_{i1}^2}h_{i1}^T h_{i1} - \sigma_{i1}\hat{\varphi}_{i1}. \tag{26}$$

From (22)-(26), we have

$$\dot{V}_{i2} \le g z_{i2} z_{i3} - \frac{z_{i1}z_{i2}}{z_{i1m}^2 - z_{i1}^2} - k_{i2}z_{i2}^2 + \frac{a_{i1}^2}{2} + \frac{b_{i1}^2\varepsilon_{i1m}^2}{2} + \tilde{\varphi}_{i1}\frac{z_{i1}^2}{2a_{i1}^2}h_{i1}^T h_{i1} - \sigma_{i1}\tilde{\varphi}_{i1}\hat{\varphi}_{i1} \tag{27}$$

Step3.

The derivative of (17) is

$$\begin{aligned}\dot{V}_{i3} &= \frac{\partial V_{i3}}{\partial z_{i3}}\dot{z}_{i3} + \frac{\partial V_{i3}}{\partial \alpha_{i2}}\dot{\alpha}_{i2} + \tilde{\varphi}_{i2}\dot{\tilde{\varphi}}_{i2} \\ &= \frac{\mu_{im}^2}{\mu_{im}^2 - \mu_i^2} z_{i3}\theta_i\left(\frac{r_i}{j_i v_i}T_i + f_{i2}\right) + \frac{\mu_{im}^2}{\mu_{im}^2 - \mu_i^2} z_{i3}\left(W_{i2}^{*T}h_{i2} + \varepsilon_{i2}\right) + \tilde{\varphi}_{i2}\dot{\tilde{\varphi}}_{i2},\end{aligned} \tag{28}$$

Design the control law as

$$T_i = \frac{j_i v_i}{r_i}\Big[-k_{i3}z_{i3} - f_{i2} - \frac{z_{i3}}{\underline{\theta}_i}\frac{\mu_{im}^2}{\mu_{im}^2 - \mu_i^2}\left(\frac{\hat{\varphi}_{i2}}{2a_{i2}^2}h_{i2}^T h_{i2} + \frac{1}{2b_{i2}^2}\right)\Big], \tag{29}$$

with the adaptive law

$$\dot{\hat{\varphi}}_{i2} = \frac{z_{i3}^2}{2a_{i2}^2}\left(\frac{\mu_{im}^2}{\mu_{im}^2 - \mu_i^2}\right)^2 h_{i2}^T h_{i2} - \sigma_{i2}\hat{\varphi}_{i2}, \tag{30}$$

Then we have

$$\dot{V}_{i3} \le -k_{i3}z_{i3}^2 - g z_{i2}z_{i3} + \sigma_{i2}\tilde{\varphi}_{i2}\hat{\varphi}_{i2} + \frac{a_{i2}^2}{2} + \frac{b_{i2}^2\varepsilon_{i2m}^2}{2}. \tag{31}$$

Thorem1. *Consider the train system (14) with the assumptions. If the control law (29) and the virtual control law (20)(25) with the adaptive law (26)(30) are implemented, then*

1) *The uniformly ultimate bounded position and velocity tracking is ensured;*
2) *The constraints of coupler force and anti-slip condition are not violated if the initial conditions are satisfied.*

Proof. From (15)-(18),(21),(27) and (31) we obtain

$$\begin{aligned}\dot{V}_i &= \dot{V}_{i1} + \dot{V}_{i2} + \dot{V}_{i3} \\ &\le -\frac{k_{i1}z_{i1}^2}{z_{i1m}^2 - z_{i1}^2} - k_{i2}z_{i2}^2 - k_{i3}z_{i3}^2 + \frac{a_{i1}^2}{2} + \frac{a_{i2}^2}{2} \\ &\quad + \frac{b_{i1}^2\varepsilon_{i1m}^2}{2} + \frac{b_{i2}^2\varepsilon_{i2m}^2}{2} + \sigma_{i1}\tilde{\varphi}_{i1}\hat{\varphi}_{i1} + \sigma_{i2}\tilde{\varphi}_{i2}\hat{\varphi}_{i2} \\ &\le -\rho_i V_i + c_i,\end{aligned} \tag{32}$$

where

$\rho_i = \min\{2k_{i1}, 2k_{i2}, 2k_{i3}, 2\sigma_{i1}, 2\sigma_{i2}\}$,

$$c_i = \frac{a_{i1}^2}{2} + \frac{a_{i2}^2}{2} + \frac{b_{i1}^2\varepsilon_{i1m}^2}{2} + \frac{b_{i2}^2\varepsilon_{i2m}^2}{2} + \frac{1}{2}\sigma_{i1}\varphi_{i1}^2 + \frac{1}{2}\sigma_{i2}\varphi_{i2}^2$$

By Lemma 1, we can obtain the results of uniformly ultimate bounded position and velocity tracking.

It is not difficult to prove by the barrier Lyapunov function that position error $z_{i1} \le z_{i1m}$ and adhesion coefficient $\mu_i \le \mu_{im}$. □

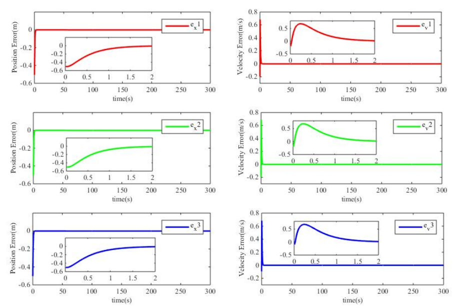

Fig.3. Position errors and velocity errors

4. Simulation Results

In this section, controller (29) will be verified for the train system (14) whose parameters are given as follows:

number of carriages $n = 3$, radius of wheels $(r_1, r_2, r_3) = (0.31, 0.31, 0.33)(m)$, inertia of wheels $(j_1, j_2, j_3) = (36, 36, 39)(kg \cdot m^2)$, mass of carriage $(m_1, m_2, m_3) = (10100, 10020, 10080)$ (kg) . The running resistance is expressed as $f_r = 1809 + 26v + 0.26v^2 + 0.1447\sin(0.02vt)$, where the last term represents the oscillation excitation force from the rail. The coupler force is calculated by $f_c = 800\xi(1 + 0.5\xi^2)$, where ξ is relative displacement between two adjacent carriages. The wheel-rail model use Burckhardt model given as $\mu = sign(\lambda)\cdot\kappa_1(1 - \exp(-\kappa_2|\lambda|)) - \kappa_3\lambda$.

The reference acceleration of the train and the parameters of Burckhardt model are as follows: $Acc = 0.6, 0 < t \le 100;\ Acc = -0.8, 200 < t \le 250;\ Acc = 0, otherwise.$
The initial state of the train is $v(0) = 11.5(m/s)$, $\omega(0) = 11.5(rad/s)$.
The performance of the controller is shown in Fig.3-4. Fig.3 indicates that position errors and velocity errors are convergent quickly. It is obvious to find that the tracking goals and coupler force constraints are satisfied. As shown in Fig.4, adhesion coefficient satisfies the requirement of antiskid control, $|\mu| \le \mu_{max}$. shows the position error and velocity error of each carriage of a train.

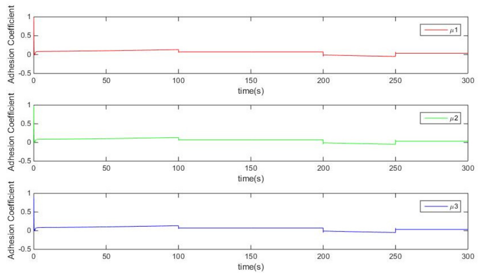

Fig.4. Adhesion coefficient of each carriage

5. Conclusions

In this paper, a neuro-adaptive controller is designed for train dynamic system with considering the uncertain nonlinear wheel-rail relationship. By using the barrier Lyapunov methods and backstepping designing methods, the tracking errors are convergent in a small region. The effect of the proposed controller is validated through the numerical simulation.

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