

Neuroadaptive Variable Structure Control of Mass Transit Trains

Qing Gu, Tao Tang and Yongduan Song*

Abstract—With the rapid development of mass transit system, how to improve the control accuracy of the train become increasingly important. During the train's running process, the resistance force is changing with some factors, such as, speed and track geometry, and these factors play an important role in tracking accuracy. Most existing methods assume the resistance force is available for feedback control or consider constant resistance coefficients. Contrasted to these methods, a neuroadaptive variable structure controller for automatic train speed and position tracking under varying operation conditions is proposed in this paper. We consider the case that the basic resistance forces and additional resistance forces are both time-varying and unknown. This method is proposed to achieve high precision position and speed tracking. The fundamental principle of this method is to design the control using combination of neural network and adaptive variable structure technique.

I. INTRODUCTION

AUTOMATIC Train Operation (ATO) system is crucial for safe, energy-saving and reliable operation of mass transit train. One of the fundamental functions of ATO is to run the train automatically according to the given pre-planned schedules, which are usually related to system operation efficiency, punctuality, energy-saving and stop precision [1]-[4]. For high-performance control of a train system in terms of accuracy, stability, and robustness, it is important to tackle the control problem exploiting the system's natural structure imposed by the physical character and considering the torques and forces acting upon it. Various control methods for train have been reported in literature during the past few years. Early control design was based on classical linear control techniques (see [5] and references therein). To address the nonlinear characteristics in the system, feedback linearization method combined with fuzzy logic control is used in [1]-[3]. To take care of the inherent model nonlinearities, researchers have investigated nonlinear control techniques. Recently, nonlinear and adaptive control methods are proposed to deal with nonlinear resistance force in the system [4], where unknown but constant resistance

coefficients are considered. Because it is insensitive to dynamic uncertainties and external disturbance, variable structure control gained widely applications [5]-[8]. Elimination of inherent chattering problems has been well addressed in [10]-[14].

In this work, we use neural network (NN) adaptive control combined with variable structure control to design position and velocity tracking control for mass transit train. The controller is synthesized using a proportional plus derivative control coupled with an online adaptive neural module, which acts as a dynamic compensator to counteract inherent model discrepancies, strong nonlinearities, and coupling effects, arisen from resistive forces, in-train forces and external disturbances due to varying railway conditions. The closed-loop stability issues of this combined control scheme are analyzed using a Lyapunov-based method. The neuroadaptive VSC approach can guarantee the uniform ultimate bounds of the tracking errors and bounds of NN weights. The control algorithms are tested and verified via computer simulations in the presence of parametric uncertainties and severe operation conditions.

II. TRAIN DYNAMIC MODEL

The dynamics of a train system can be described by the following differential equation

$$M\dot{x} = F - f_b(\cdot) - f_a(\cdot) \pm \varphi(\cdot) \quad (1)$$

where

F - the control force of the train (traction or braking force);

M - the equivalent mass of the train;

x - the position/displacement of the train ;

$f_b(\cdot)$ - the basic resistance force;

$f_a(\cdot)$ - the additional resistive force (due to tunnel, curvature, railway ramp etc);

$\varphi(\cdot)$ - interactive impact from the adjacent vehicles on the leading vehicle.

Note that the underlying dynamic model as presented in (1) explicitly takes into account the impact from the adjacent vehicles on the leading one. Such impact is generally difficult to model precisely in practice, which, together with the fact that the basic and additional resistive forces are nonlinear and known, calls for more dedicated control design for position and velocity tracking. In this work we develop a control scheme by integrating neural networks into variable structure control.

Manuscript received November 28, 2010. This work was supported by the state key laboratory of rail traffic control and safety (Beijing Jiaotong University) under the project RCS2008ZZ001 and National Natural Science Foundation of China No.60634010 and No. 60974052.

Qing Gu is with the State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China (karengqq@gmail.com)

Tao Tang is with the State Key Laboratory of Rail Traffic Control and Safety, Beijing Jiaotong University, Beijing, China (ttang@bjtu.edu.cn).

Yongduan Song is with the State Key Laboratory of Rail Traffic Control and Safety, Center for Intelligent Systems and Renewable Energy, Beijing Jiaotong University, Beijing, China (*corresponding author:010-51684432; fax: 010-51684432; e-mail: ydsong@bjtu.edu.cn)

III. CONTROL DESIGN AND STABILITY ANALYSIS

Define the position tracking error $e = x - x^*$, where x^* is the desired position of the train. To develop a control scheme for both position and velocity tracking, we introduce a filtered variable as follows:

$$s = \dot{e} + \beta e \quad (2)$$

where $\beta > 0$ is a free design constant chosen by the designer. In light of (2), the position and velocity tracking control problem can be converted into the stabilization problem of the following filtered error dynamics

$$M\dot{s} = F + H_d(\cdot) \quad (3)$$

with

$$H_d(\cdot) = -f_b(\cdot) - f_a(\cdot) \pm \varphi(\cdot) + M(\beta\dot{e} - \ddot{x}^*) \quad (4)$$

A. Model based Control

Under the assumption that $H_d(\cdot)$ is completely available, the following model based control can be derived

$$F = -k_0 s - H_d(\cdot) \quad (5)$$

where $k_0 > 0$ is a design constant. It is readily verified that the control scheme is able to ensure asymptotic position and velocity tracking as long as $H_d(\cdot)$ is computable. However, as indicated by the expression of $H_d(\cdot)$, it is rather difficult, if not impossible, to obtain such term precisely. Therefore, the control law (6) is impractical. In next section a control scheme based on neuroadaptive approximation on the lumped uncertainties is developed.

B. Neuroadaptive Variable Structure Control

Four cases are considered:

Case 1) $H_d(\cdot)$ is unknown but slowly time-varying.

Case 2) $H_d(\cdot)$ can be parameterized into the form of

$$H_d(\cdot) = \sum_{i=1}^l \eta_i(x, \dot{x}) p_i \quad (6)$$

where $\eta_i(x, \dot{x})$ is some bounded known (possibly nonlinear) function and p_i is some unknown constant.

Case 3) $H_d(\cdot)$ is completely unknown and time-varying.

Case 4) $H_d(\cdot)$ is a combination of case 2) and Case 3).

Theorem 1 (Control Scheme I)

Consider the train dynamics as describe by (1) with the assumption as in Case 1). If the control force is designed as

$$F = -k_0 s - k_1 \int_0^t s d\tau \quad (7)$$

where $k_0 > 0$ and $k_1 > 0$ are two control design parameters. Then asymptotic position and velocity tracking is ensured.

Proof:

From (3) and (7), one has

$$M\dot{s} = -k_0 s - k_1 \int_0^t s d\tau + H_d(\cdot) \quad (8)$$

Under the assumption that $H_d(\cdot)$ is slowly time-varying, one can express (8) as

$$M\ddot{s} + k_0 \dot{s} + k_1 s = 0$$

The result follows by using the fact that $M > 0$, $k_0 > 0$, $k_1 > 0$ and $\dot{H}_d = 0$.

Remark 1

The control scheme does not involve the mass of the train, nor any other information of the system, which makes it fairly easy to implement. However, the effectiveness of the control relies on the assumption that $H_d(\cdot)$ is slowly time-varying.

Theorem 2 (Control Scheme II)

Consider the train dynamics as describe by (1) with the assumption as in Case 2). If the control force is designed as

$$F = -k_0 s - \sum_{i=1}^l \eta_i(x, \dot{x}) \hat{p}_i \quad (9)$$

with

$$\hat{p}_i = \gamma_0 \int_0^t s \eta_i(x, \dot{x}) dt + \gamma_1 s \eta_i(x, \dot{x}) \quad (10)$$

where $k_0 > 0$, $\gamma_0 > 0$ and $\gamma_1 > 0$ are control design parameters. Then asymptotic position and velocity tracking is ensured.

Proof:

The result can be easily shown by using the Lyapunov function candidate

$$V = \frac{1}{2} Ms^2 + \frac{1}{2\gamma_0} \sum_{i=1}^l (p_i - \hat{p}_i + \gamma_1 \eta_i s)^2$$

which leads to

$$\dot{V} = -k_0 s^2 - \gamma_1 \sum_{i=1}^l (\eta_i s)^2 \leq 0$$

which implies that $s \in L_\infty \cap L_2$, $\hat{p}_i \in L_\infty$. Furthermore, we can show that F is bounded $\dot{s} \in L_\infty$, i.e., s is uniformly continuous. It is then concluded with Babarlet lemma that $s \rightarrow 0$ as $t \rightarrow \infty$. Hence by the definition of s , we have

$e \rightarrow 0$ and $\int edt \rightarrow 0$ as $t \rightarrow \infty$. Namely, both position and speed tracking is ensured.

Remark 2

The control scheme is build upon the availability of the function $\eta_i(x, \dot{x})$. This demands certain analytical manipulation of the lumped uncertainty $H_d(\cdot)$. Such parameterization process might be time-consuming in practice. The next control scheme utilizes the universal approximation capability of neural networks to copy with the lumped uncertainty of the system directly.

Theorem 3 (Control Scheme III)

Consider the train dynamics as describe by (1) with the assumption as in Case 3). If the control force is designed as

$$F = -k_0 s - \sum_{i=1}^l \phi_i(x, \dot{x}) \hat{w}_i + u_{vsc} \quad (11)$$

with

$$u_{vsc} = -\hat{\varepsilon}_0 \text{sign}(s) \quad (12)$$

where the weights \hat{w}_i ($i = 1, 2, \dots, l$) and $\hat{\varepsilon}_0$ are updated by

$$\dot{\hat{w}}_i = \gamma_0 \int_0^t s \phi_i(x, \dot{x}) dt + \gamma_1 s \phi_i(x, \dot{x}) \quad (13)$$

$$\dot{\hat{\varepsilon}} = \gamma_2 |s| \quad (14)$$

where $\phi_i(\cdot)$ is the basis function the i^{th} neuron, $k_0 > 0$, $\gamma_0 > 0$ and $\gamma_1 > 0$ and $\gamma_2 > 0$ are control design parameters. Then asymptotic position and velocity tracking is ensured.

Proof:

With the NN approximation mechanism, it holds that there exist an optimal NN of the form $\sum_{i=1}^l \phi_i w_i$ that is able to approximate $H_d(\cdot)$ with sufficient accuracy. Namely,

$$H_d(\cdot) = \sum_{i=1}^l \phi_i w_i + \varepsilon \quad (15)$$

with the reconstruction error satisfying $|\varepsilon| \leq \varepsilon_0 < \infty$, where ε_0 is constant but unknown. This leads to the following closed loop dynamics if the proposed control (11) is applied,

$$M\dot{s} = -k_0 s + \sum_{i=1}^l (w_i - \hat{w}_i) \phi_i + \varepsilon + u_{vsc} \quad (16)$$

Consider the Lyapunov function candidate

$$V = \frac{1}{2} Ms^2 + \frac{1}{2\gamma_0} \sum_{i=1}^l (w_i - \hat{w}_i + \gamma_1 \phi_i s)^2 + \frac{1}{2\gamma_2} (\varepsilon_0 - \hat{\varepsilon}_0)^2$$

It follows that

$$\begin{aligned} \dot{V} &= -k_0 s^2 + \sum_{i=1}^l (w_i - \hat{w}_i) \phi_i s + s(u_{vsc} + \varepsilon) \\ &+ \frac{1}{\gamma_0} \sum_{i=1}^l (w_i - \hat{w}_i + \gamma_1 \phi_i s) \left[-\dot{\hat{w}}_i + \gamma_1 \frac{d}{dt}(\phi_i s) \right] \\ &+ \frac{1}{\gamma_2} (\varepsilon_0 - \hat{\varepsilon}_0) (-\dot{\hat{\varepsilon}}_0) \end{aligned}$$

Using (16) in which the u_{vsc} as defined as in (12), it is not difficult to show that

$$\dot{V} = -k_0 s^2 - \gamma_1 \sum_{i=1}^l (\phi_i s)^2 \leq 0$$

The result is established with the same argument as in the proof Theorem 2.

Remark 3

It is seen that the proposed control is independent of explicit information on faults and disturbances. As with most variable structure control methods, when the states get s closer to zero, the control scheme might experience chattering,

which can be easily avoided by replacing $\frac{s}{\|s\|}$ with $\frac{s}{\|s\| + \mu_0}$,

where μ_0 is a small number, as commonly adopted in the literature. Also to prevent the estimate from drifting, a damping term similar to that used in [3] can be used. In this case, we have the following ultimately uniformly bounded (UUB) tracking result.

As the basic resistance force mainly consists of friction and aerodynamic drag, which is proportional to train speed (\dot{x}) and square of train speed, respectively. Therefore, the lumped uncertainty $H_d(\cdot)$ can actually decomposed into two parts, one is of the form

$$a_0 + a_1 \dot{x} + a_2 \dot{x}^2$$

for some unknown constants. a_0, a_1 and a_2 . Therefore a different control scheme can be built based on such structural feature of $H_d(\cdot)$, as stated in the following theorem.

Theorem 4 (Control Scheme IV)

Consider the train dynamics as describe by (1) with the assumption as in Case 4). If the control force is designed as

$$F = -k_0 s - (\hat{a}_0 + \hat{a}_1 \dot{x} + \hat{a}_2 \dot{x}^2) - \sum_{i=1}^l \hat{w}_i \phi_i + u_{vsc} \quad (17)$$

with

$$u_{vsc} = -\hat{\varepsilon}_0 \text{sign}(s) \quad (18)$$

where the weights \hat{a}_i ($i = 0, 1, 2$), \hat{w}_i ($i = 1, \dots, l$) and $\hat{\varepsilon}_0$ are updated by

$$\begin{aligned} \dot{\hat{a}}_0 &= \gamma_0 s \\ \dot{\hat{a}}_1 &= \gamma_0 \dot{x} s \\ \dot{\hat{a}}_2 &= \gamma_0 \dot{x}^2 s \\ \dot{\hat{w}}_i &= \gamma_1 \phi_i s \\ \dot{\hat{\varepsilon}}_0 &= \gamma_2 |s| \end{aligned} \quad (19)$$

where $k_0 > 0$ and $\gamma_0 > 0$, $\gamma_1 > 0$, $\gamma_2 > 0$ are control design parameters. Then asymptotic position and velocity tracking is ensured.

Proof:

The result can be readily shown by considering the following Lyapunov function candidate

$$V = \frac{1}{2} M \dot{s}^2 + \frac{1}{2\gamma_0} \sum_{i=0}^2 (a_i - \hat{a}_i)^2 + \frac{1}{2\gamma_1} \sum_{i=1}^l (w_i - \hat{w}_i)^2 + \frac{1}{2\gamma_2} (\varepsilon_0 - \hat{\varepsilon}_0)^2$$

and follow the same lines as in the proof of Theorem 3, we could get

$$\dot{V} = -k_0 s^2 \leq 0$$

The result is established with the same argument as in the proof Theorem 2.

IV. SIMULATION AND VERIFICATION

In order to visualize the efficacy of the control scheme, numerical simulation tests in the presence of different operation conditions and parametric uncertainties are performed using the original train model (1) with parameters given as in Table 1 and Table 2.

Table 1 Parameters of train operation conditions

Inter-station distance (m)	Schedule time (s)	Limit speed (km/h)	Tracking mass (t)
1200	92	70	189

Table 2 Track layout of the inter-station run

Section(m)	0~200	200~800	800~1200
gradient	4‰	0	1‰

The design parameters in this simulation are chosen as

$$k_0 = 250, \gamma_0 = 5, \gamma_2 = 1 \text{ and } \beta = 1.$$

The unit basic resistance used in the simulation is

$$f_b = 2.0(1 + |\sin(0.1t)|) + 0.55(1 + |\cos(0.4t)|)\dot{x} + 0.56(1 + |\sin(0.1t)|)\dot{x}^2$$

in which time-varying resistance coefficients are involved. The additional force simulated is set as

$$f_a = \begin{cases} 1.5|x| & t < t_1 \\ 0.5(1 + |\cos(0.4\dot{x})|)\dot{x} & t_1 \leq t < t_2 \\ \frac{1.6(1 + |\sin(0.1t)|)}{1 + |\dot{x}| + \dot{x}^2} & t_3 \leq t < t_f \end{cases}$$

arisen from other additional resistance. For simulation purpose, we consider the case that the spring deformation of the coupler varies according to the following relations,

$$\varphi(\cdot) = \alpha_0 x_d + \alpha_1 \dot{x}_d + \alpha_2 |\dot{x}_d|^2$$

with

$$\Delta x_{d1} = \Delta x_{d3} = \Delta x_{d4} = 0.1 \sin t \text{ (mm)},$$

$$\Delta x_{d6} = \Delta x_{d7} = 0.15 \cos t \text{ (mm)},$$

$$\Delta x_{d2} = \Delta x_{d5} = 0.1 \cos t \text{ (mm)}.$$

The effectiveness of the proposed control scheme (11) is put into test in this section. The simulation results are shown in Fig. 1- Fig. 4, where Fig. 1 is the objective v-s profile. With the proposed control scheme, the tracking performance is shown in Fig.2. One can observe high precision tracking in position and speed during the entire operation. The compensating control signal is shown in Fig. 4. Overall, it is confirmed that the proposed control ensures fairly good control performance in terms of accuracy and robustness.

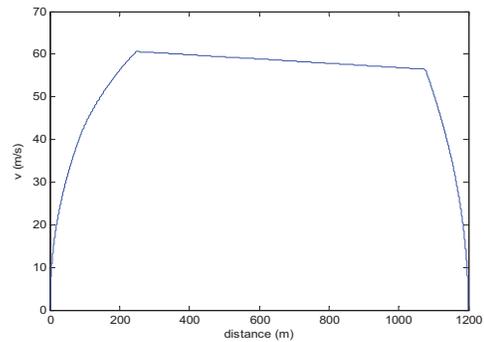


Fig. 1. Ideal speed versus position (v-s) profile

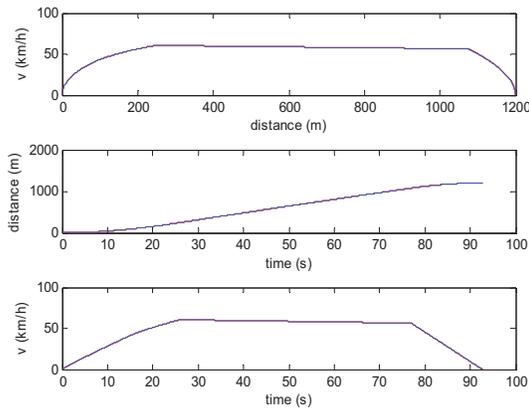


Fig. 2. Speed and position tracking performance

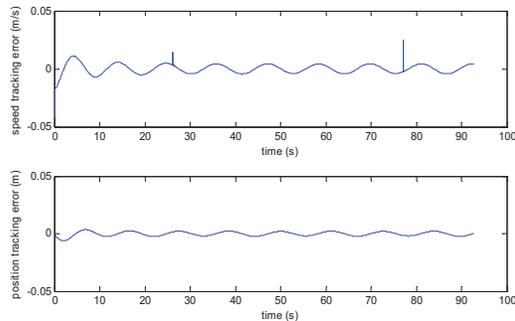


Fig. 3. Speed and position tracking error

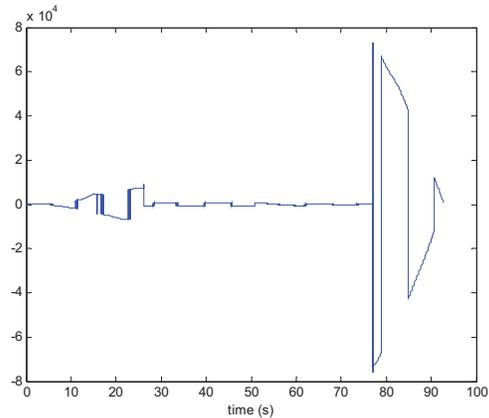


Fig. 4. The rate of compensator (u_{vsc})

V. CONCLUSION

Speed and position tracking control problem of mass transit train is investigated in this work. Neuroadaptive variable structure control algorithms are developed to ensure high precision tracking control of train under varying operation conditions. Simulation results in the face of model parametric uncertainties and instantaneous road curvature changes show the stability and robustness of the control algorithm. The model that was used for dynamic simulations

has strong nonlinearities and highly coupled dynamics. We observed that the proposed scheme maintained the tracking accuracy, stability, and ride comfort of the train motion even under adverse operation conditions

REFERENCES

- [1] S. Yasunobu, S. Miyamoto, "Automatic train operation systems by predictive fuzzy control", Industrial Applications of Fuzzy Control, North-Holland, Amsterdam (1985), pp. 1-18.
- [2] S. Yasunobu, S. Miyamoto, H. Ihara. "A fuzzy control for train automatic stop control", Trans. of the Society of Instrument and Control Engineers. Vol. E-2, No.1, 1/9(2002).
- [3] Qi Song, Qing Gu, Feng Liu and Y. D. Song, "Adaptive Positioning and Velocity Control of High Speed Train System", 2009 China Automation Association Conference (CAAC), Hangzhou, China, November 2009.
- [4] Y.H. Wang, B. Ning and Y. D. Song, "Traction and Braking Auto-Control of High Speed Train systems", 2009 China Automation Association Conference (CAAC), Hangzhou, China, November 2009.
- [5] Qing Gu, T. Tang and Y. D. Song, "Smooth Variable Structure Control of train Systems", 2010 Chinese Decision and Control Conference, Xuzhou, China. pp. 3239 - 3244.
- [6] D. Manicini, M. Brescia, E. Cascone, and P. Schipani, "A Variable Structure Control JAW for Telescopes Pointing and Tracking", in Acquisition, Tracking, and pointing XI, ed. M. K. Masten, L.A. Stockum, Proc. SPIE 3086,1997, pp. 72-84.
- [7] C. Scali, G. Nardi, A. Landi, and A. Balestrino, "Performance of Variable Structure PI controllers in Presence of Uncertainty and Saturation nonlinearities", XII IFAC World Congress, Sidney, Australia, Vol. 8, 1993. pp. 527-532.
- [8] K. S. Yeung and Y. P. Chen, "A New Controller Designed for Manipulators Using the Theory of Variable Structure Systems," IEEE Trans. Automat. Control. 33, 1988, pp.200-206.
- [9] Baocheng Hui, Simulation Study of Variable Structure control in The Auto Control System of Train., Master Degree Thesis, Southwest Jiaotong University, PRC 2003.
- [10] W. Gao and J. C. Hung, "Variable Structure Control of Nonlinear System: A New Approach", IEEE Trans. Industrial Electronics, Vol.40, Feb.1993, pp. 45-55.
- [11] S. W. Pan, H. Y. Su, X. Hu, J. A. Chu, "Variable Structure Control Theory and Application: a Survey," IEEEProc, Vol. 4, 2000.
- [12] J. Y. Hung, W. Gao, and J. C. Hung, "Variable Structure Control: a Survey," IEEE Trans Ind. Electron 40(1), 1993, pp. 2-22.
- [13] X. H. Liao, W. C. Cai, M. J. Zhang, and Y. D. Song, "Smooth Variable Structure Attitude Control of Crew Exploration Vehicles Driven by Nonlinear Actuators", 2007 AIAA Navigation, Guidance and Control, Conference and Exhibit, 7 - 10 May 2007,.
- [14] Y. D. Song, X. Liao, Z. Sun, and Y. Li, "A New Approach to Eliminating Variable Structure Control Chattering with Application to Flight Vehicles", 2004 IEEE Symposium on Systems Theory, 2004. pp.59-63.