Expert Systems with Applications 37 (2010) 2016–2027

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Adaptive intelligent backstepping longitudinal control of vehicle platoons using output recurrent cerebellar model articulation controller

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ARTICLE INFO

Keywords:
Backstepping control
Vehicle-following control
Adaptive control
Output recurrent cerebellar model articulation controller

ABSTRACT

Automatic vehicle-following on traffic safety has been an active area of research. This paper is concerned with the adaptive intelligent backstepping longitudinal control (AIBLC) system for the vehicle-following control of a platoon of automated vehicles. In the proposed control system, an adaptive output recurrent cerebellar model articulation controller (ORCMAC) is used to mimic an ideal backstepping control and a robust controller is designed to attenuate the effects caused by lumped uncertainty term (such as unmodeled dynamics, external disturbances and approximate errors), so that the H^{∞} tracking performance can be achieved. Moreover, the Taylor linearization technique is employed to derive the linearized model of the ORCMAC. The adaptation laws of the AIBLC system are derived on the basis of the Lyapunov stability analysis and H^{∞} control theory so that the stability of the closed-loop system can be guaranteed. Finally, the simulation results denominate that the proposed AIBLC system can achieve favorable tracking performance for a safe vehicle-following control.

1. Introduction

Transportation technology is one of the most significant areas on the human life. During manual driving, most human drivers often use information about the speed and position of the leading and following vehicles in order to adjust the position and speed of their vehicles. Since many of today's automobile accidents are caused by human error, automating the driving process may actually increase the safety of the highway. Therefore, the automatic vehicle-following control objective is to maintain a desired safety space from its leading vehicle as well as driving comfort. Recently much effort has been spent on various control laws for a platoon of vehicles (Caudill & Garrard, 1997; Fujioka & Suzuki, 1994; Lee & Kim, 2002; No, Chong, & Roh, 2001; Sheikholeslam & Desoer, 1992; Spooner & Passino, 1996; Swaroop, Hedrick, & Choi, 2001; Zhang, Kosmatopoulos, Ioannou, & Chien, 1999). In Zhang et al. (1999), an autonomous intelligent cruise control law is proposed that uses relative speed and spacing measurements from both the vehicle in front and vehicle behind. The controller guarantees vehicle stability as well as platoon stability for both time headway and space headway policies without using preview information about the platoon leader. Spooner and Passino (1996) presented an adaptive control for vehicle-following control system. They assume that the nominal model of the vehicle system is known. The control system consists of a main controller and an adaptive fuzzy controller. The known main controller reveals a basic stabilizing controller to stabilize the system and the adaptive fuzzy controller presents a compensating controller to compensate for the difference between an ideal controller and main controller. Sheikholeslam and Desoer (1992) proposed longitudinal controllers using exact linearization methods to linearize and normalize the input–output behavior of each vehicle in the platoon. Fujioka and Suzuki (1994) used sliding mode control schemes as well as feedback linearization techniques based on nonlinear vehicle models. However, these model based approaches have some drawbacks. The fact that different kinds of vehicles may require different model structures and parameters becomes a heavy burden to the designer. Moreover the performance of the platoon can be significantly degraded due to model mismatches, parametric uncertainties or disturbances.

Recently, powerful approximation capabilities of neural networks (NNs) for identification and control of dynamic systems have motivated intensive research for their applications (Hung & Chung, 2007; Ku & Lee, 1995; Kuschewski, Hui, & Zak, 1993; Lin & Hsu, 2002, 2004; Lin, Wai, Chou, & Hsu, 2002). According to the structure, the NNs can be mainly classified as feedforward neural networks (FNNs) (Hung & Chung, 2007; Kuschewski et al., 1993; Lin & Hsu, 2002) and recurrent neural networks (RNNs) (Ku & Lee, 1995; Lin & Hsu, 2004; Lin et al., 2002). As known, the FNN is a static mapping. Without the aid of tapped delays, the FNNs are unable to represent a dynamic mapping. For the RNNs, of particular interest is their ability to deal with time varying input or output through their own natural temporal operation (Ku & Lee,

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doi:10.1016/j.eswa.2009.06.055

1995). The RNN is a dynamic mapping and demonstrates good control performance in the presence of unmodelled dynamics (Lin & Hsu, 2004; Lin et al., 2002). However, no matter for the FNNs or RNNs, the learning is slow since all the weights are updated during each learning cycle. Therefore, the effectiveness of the NN is limited in problems requiring on-line learning.

The cerebellar model articulation controller (CMAC) is classified as a non-fully connected perceptron-like associative memory network proposed by Albus (1975, 1975). The CMACs have been adopted widely for the closed-loop control of complex dynamical systems owing to its fast learning property, good generalization capability, and simple computation compared with the neural network (Chen, Lin, & Chen, 2008; Chiang & Lin, 1996; Kim & Lewis, 2000; Lane, Handelman, & Gelfand, 1992; Lin & Peng, 2004, 2005). This network has been already validated that it can approximate a nonlinear function over a domain of interest to any desired accuracy. The contents of these memory locations are referred as weights, and the output of this network is a linear combination of these weights in the memory addressed by the activated inputs (Lane et al., 1992). The conventional CMAC uses local constant binary receptive-field basis functions. The disadvantage is that its output is constant within each quantized state and the derivative information is not preserved. Therefore, Chiang and Lin (1996) developed a CMAC with non-constant differentiable Gaussian receptive-field basis function, and provided the convergence analyses of this network. Some applications of CMAC for nonlinear systems have been presented in Chen et al. (2008), Kim and Lewis (2000) and Lin and Peng (2004, 2005). However, the major drawback of the existing CMACs is that their application domain is limited to static problem due to their inherent network structure. To tackle this problem, an output recurrent cerebellar model articulation controller (ORCMAC) is proposed, which includes the delayed recurrent units in the conventional CMAC. Thus, ORCMAC presents a dynamic CMAC.

The backstepping control technique is a systematic and recursive design methodology for nonlinear systems. Numerous backstepping control design procedures have been proposed in the literature for systems (Choi & Farrell, 2001; Krstic, Kanellakopoulos, & Kokotovic, 1995; Lin et al., 2002; Wai, Lin, Duan, Hsieh, & Lee, 2002; Zhang, Ge, & Hang, 2000). The idea of backstepping design is to select recursively some appropriate functions of state variables as pseudo-control inputs for lower dimension subsystems of the overall system. Each backstepping stage results in a new pseudo-control design, expressed in terms of the pseudo-control design from preceding design stages. The procedure terminates a feedback design for the true control input which achieves the original design objective by virtue of a final Lyapunov function which is formed by summing the Lyapunov functions associated with each individual design stage (Lin et al., 2002; Wai et al., 2002; Zhang et al., 2000).

Because the dynamics of vehicle systems are apparently of highly complex nature and are difficult to be modeled accurately, it is difficult to design a conventional control scheme for the automated vehicle-following control system. In this paper, an adaptive intelligent backstepping longitudinal control (AIBLC) system is investigated for the vehicle-following control of a platoon of automated vehicles to achieve the H^∞ tracking performance. The developed AIBLC system is comprised of an adaptive ORCMAC and a robust controller. The adaptive ORCMAC is used to mimic an ideal backstepping control and a robust controller is designed to attenuate the effects caused by lumped uncertainty, so that the H^∞ tracking performance can be achieved (Chen & Lee, 1996; Liu & Li, 2003; Wang, Chan, Hsu, & Lee, 2002). Moreover, the Taylor linearization technique is employed to derive the linearized model of the ORCMAC. The on-line adaptation laws of the AIBLC system are derived on the basis of the Lyapunov stability analysis and H^∞ control theory so that the stability of the closed-loop system can be guaranteed. Finally, the simulation results denominate that the proposed AIBLC system can achieve favorable tracking performance for a safe vehicle-following control. The study is organized as follows. Problem statement is presented in Section 2. The structure of ORCMAC is described in Section 3. The design procedures of the proposed AIBLC system are constructed in Section 4. Simulation results are provided to validate the effectiveness of the proposed control system in Section 5. Conclusions are drawn in Section 6.

2. Problem statement

2.1. Platoon model

Fig. 1 describes a platoon of N vehicle following a leading vehicle on a straight lane of highway (Sheikholeslam & Desoer, 1992). The safety spacing of the ith vehicle in the platoon is denoted by H_i. The abscissa of the rear bumper of the$i$th vehicle with respect to a fixed reference point Oon the road is denoted by x_i. The position of the lead vehicle's rear bumper with respect to the same fixed reference point is denoted by x_L. From the platoon configuration, the spacing error e_i can be written as:

$$e_i = \begin{cases} x_L - x_1 - H_1, & \text{for } i = 1 \\ x_{i-1} - x_i - H_i, & \text{for } i = 2, 3, \ldots, N \end{cases} \tag{1}$$

2.2. Longitudinal vehicle model

The longitudinal dynamics of the ith vehicle in the platoon are modeled as follows (for $i = 1, 2, \ldots, N$)

$$\dot{\xi}_i = \frac{1}{\tau_i(\upsilon_i)}(-\xi_i + u_i) \tag{2}$$

$$\dot{\upsilon}_i = a_i = \frac{1}{M_i}(\xi_i - K_{di}\upsilon_i^2 - d_{mi}) \tag{3}$$

where ξ_i denotes the driving/braking force produced by the ith vehicle engine; $\upsilon_i = \dot{x}_i$ denotes the velocity of the ith vehicle; τ_i represents the engine/brake time lag of the ith vehicle; u_i specified the control input of the ith vehicle's engine (if $u_i > 0$, then it represents a throttle input and if $u_i < 0$, it represents a brake input); a_i denotes the acceleration of the ith vehicle; M_i is the mass of the ith vehicle; K_{di} denotes the aerodynamic drag coefficient for the ith vehicle; and d_{mi} denotes the ith vehicle's mechanical drag. Eq. (2) represents the ith vehicle's engine dynamics and (3) represents Newton's second law applied to the ith vehicle modeled as a particle of mass M_i. Differentiating both sides of (3) with respect to time and substituting the expression for f_i in term of υ_i and a_i from (2) and (3), it is obtained that

$$\dot{a}_i = f_i(a_i, \upsilon_i) + g_i(\upsilon_i)u_i \tag{4}$$

where $f_i(a_i, \upsilon_i) = -\frac{1}{\tau_i(\upsilon_i)}\left[a_i + \frac{K_{di}}{M_i}\upsilon_i^2 + \frac{d_{mi}}{M_i}\right] - \frac{2K_{di}}{M_i}\upsilon_i a_i$ and $g_i(\upsilon_i) = \frac{1}{M_i\tau_i(\upsilon_i)}$. Assuming that all the parameters of the system are well known, the nominal model of nonlinear systems (4) can be represented as

$$\dot{a}_i = f_{oi}(a_i, \upsilon_i) + g_{oi}u_i \tag{5}$$

where $f_{oi}(a_i, \upsilon_i)$ is the nominal value of $f_i(a_i, \upsilon_i)$, and $g_{oi} > 0$ is a nominal constant of $g_{oi}(\upsilon_i)$. If external disturbance is included and the uncertainties occur, then the system model (4) can be described as

$$\begin{aligned}\dot{a}_i &= (f_{oi}(a_i, \upsilon_i) + \Delta f_i(a_i, \upsilon_i)) + (g_{oi} + \Delta g_i(\upsilon_i))u_i \\ &= f_{oi}(a_i, \upsilon_i) + g_{oi}u_i + d_i(t)\end{aligned} \tag{6}$$

where $\Delta f_i(a_i, \upsilon_i)$ and $\Delta g_i(\upsilon_i)$ denote the uncertainties; $d_i(t)$ is referred to as the lumped uncertainty, defined as $d_i(t) \equiv \Delta f_i(a_i, \upsilon_i) + \Delta g_i(\upsilon_i)u_i$. The lumped uncertainty is assumed to be bounded with