Neuroadapтив Combined Lateral and Longitudinal Control of Highway Vehicles Using RBF Networks

Sisil Kumarawadu, Member, IEEE, and Tsu Tian Lee, Fellow, IEEE

Abstract—A neural network (NN) adaptive model-based combined lateral and longitudinal vehicle control algorithm for highway applications is presented in this paper. The controller is synthesized using a proportional plus derivative control coupled with an online adaptive neural module that acts as a dynamic compensator to counteract inherent model discrepancies, strong nonlinearities, and coupling effects. The closed-loop stability issues of this combined control scheme are analyzed using a Lyapunov-based method. The neurocontrol approach can guarantee the uniform ultimate bounds of the tracking errors and bounds of NN weights. A complex nonlinear three-degree-of-freedom dynamic model of a passenger wagon is developed to simulate the vehicle motion and for controller design. The controller is tested and verified via computer simulations in the presence of parametric uncertainties and severe driving conditions.

Index Terms—Automated highway vehicle, intelligent vehicle highway system (IVHS), lateral and longitudinal control, neural networks (NNs), vehicle dynamics.

I. INTRODUCTION

AUTOMATED vehicle control systems are a key technology for intelligent vehicle highway systems (IVHSs). An autonomous vehicle can be defined as a vehicle controlling its own steering and speed (see [1] for a recent overview). Although a considerable amount of research has been reported, for reasons underlined shortly among others, automated vehicle control leaves much to be desired.

The majority of the considerable amount of research on automated vehicle operation that the last two decades have witnessed has focused on either pure longitudinal or pure lateral control. Methods based on fuzzy inference systems (FISs) have been proposed, focusing on either purely longitudinal [2], [3] or purely lateral [4] control of vehicles (see [5]–[7] and references therein for other purely longitudinal control schemes). Lateral control has also been addressed as a separate control issue [8]–[12]. It is known, however, that the vehicle dynamics are not completely independent in both directions. In [18], it has been clearly shown that the dynamic coupling compensation does significantly improve control performance. The coupling effects become increasingly significant as maneuvers involve higher accelerations, larger tire forces, or reduced road friction [13]. Owing to this fact, although efforts have been made to merge the two control tasks into a single problem, only a few such works have been reported [14]–[21]. The inherent coupling between control inputs, net torque, and steering angle is often ignored by simplifying the dynamic equations in controller design [16]–[19]. An exact knowledge of the system dynamics is required in [20]. Kumarawadu and Lee [21] focus solely on stability issues and do not guarantee accuracy of lateral control particularly on curvy roads.

Early control design was based on classical linear control techniques (see [10] and references therein). To take care of the inherent model nonlinearities, researchers have investigated nonlinear control techniques starting in the early 1990s [9]. Sliding mode control methods have arguably been the most common [6], [7], [9], [16]–[18]. Elimination of inherent chattering problems has been well addressed. Other robust control design methods based on $H_{\infty}$ theory have been applied in [9] and [12]. A backstepping-based method to achieve robust adaptive control has been proposed in [15]. Due to the apparently complex nonlinear coupling between the net torque and the steering angle inputs in the vehicle dynamic models, simplified models in the form of either linearized or decoupled models are often used [7]–[12], [16]–[18]. Although such approximations may be valid under certain smooth steady-state operations, they may even cause divergence when the vehicle is negotiating transient situations where larger steering inputs are needed and the coupling effects are increasingly significant. Longitudinal acceleration is often assumed to be negligible in lateral control literature [11], [12].

The remarkable attention that intelligent control techniques have received recently is due to their promising learning capabilities, which have left plenty of room for further developments. For instance, direct adaptive neural network (NN)-based control has shown superior efficiency and effectiveness over the conventional adaptive control for other mechanical systems like robot systems [32]. In the field of automated vehicle control, methods based on artificial NNs have been presented for purely lateral control [8] and for purely longitudinal control [5]. The work based on learning the human driver’s response presented in [14] is the first attempt to utilize NNs for combined speed and steering control in this area. Based on experimental data, two NNs (one for speed and the other for steering) are trained completely offline to learn the input/desired output mapping. Satisfactory results have been reported under situations and environments in which training data are obtained. A quite similar approach for steering control has been adopted in [8]. However, such methods are valid only in a local region of the entire vehicle operation, can invite unexpected dangers...
under different conditions at high operating speeds, and have
no self-adaptation qualities. Furthermore, the method itself is
theoretically incomplete as closed-loop stability has not been
established. The identification and control of the nonlinear
longitudinal dynamics of an experimental lorry using a finite-
element method-based NN approach have been presented in [5].
For high-performance control of a mechanical 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
torques and forces acting upon it. However, the dynamics of
highway vehicles are apparently of highly complex nature and
difficult to model. To this end, synthesizing controllers to make
the best use of available model information and to ask NNs to
adaptively compensate for the discrepancies online is believed
to be a better strategy. Furthermore, NNs perform better when
they are asked to learn less.
NNs have shown promise in solving complex control prob-
lems [8]. This paper describes a model-based online adaptive
neurocontroller for combined lateral and longitudinal control
of highway vehicles. Closed-loop stability issues are estab-
lished through formative mathematical analysis. This paper is
inspired by the work of Kumarawadu et al. [22], wherein an
output tracking approach was proposed for high-performance
tracking control of partly known rigid revolute robot systems.
The key points of the design strategy are the possibility of
using whatever reliable model information is available while
at the same time allowing the adoption of strong learning ca-
pabilities of connectionist models (NNs) and ensuring closed-
loop stability of the combined proportional plus derivative (PD)
controller–NNs system. As far as we know, this is the first at-
tempt to solve the problem of combined lateral and longitudinal
control for highway vehicles via online adaptive neurocontrol.
A complex three-degree-of-freedom (3-DOF) dynamic
model of the “Sevrin” (Mitsubishi Motors, Taiwan, R.O.C.)
passenger wagon, which is used for real-world testing at the
ITS Center, National Chiao Tung University, Taiwan, R.O.C.,
is also derived in the sensor space for controller design and
evaluation purposes. Instead of simplistically dropping out
coupling terms, the controlled terms in the dynamic model are
separated from the rest using a simple nonlinear transformation,
and an easily manipulable intermediate model is obtained. Only
small angle approximation is used to deduce the model for
controller design hoping that the strong learning capability of
NNs will counteract the effects. The neurocontroller can then
be applied to the longitudinal and lateral dynamics, and the
resulting equations are solved for the actual control inputs.
The control approach facilitates the inclusion of the complex
nonlinear coupling effects in the controller derivation.
The rest of this paper is organized as follows: In Section II, a
nonlinear 3-DOF vehicle dynamic model is developed in sensor
space. This model is used for controller design and evaluation
in the following sections. Section III describes the complete
control structure, giving the selection criteria of controller para-
meters and adaptation laws for neural modules. Tracking error
and weight convergence issues are established via formative
mathematical analysis. Several numerical simulation test results
on straight and curvy roads under various driving conditions are
presented in Section IV to visualize the efficacy of the method.
Section V concludes this paper.

II. BACKGROUND AND SYSTEM DESCRIPTION
Some mathematical preliminaries and a stability notion that
will be used in the later sections are stated first. Let \( \mathbb{R} \) denote
real scalars and \( \mathbb{R}^n \) denote real \( n \) vectors. The absolute value of
a scalar \( x \in \mathbb{R} \) is defined as

\[ |x| = x \sgn(x), \quad \sgn(\cdot) = \begin{cases} 1, & \text{if } (\cdot) > 0 \\ 0, & \text{if } (\cdot) = 0 \\ -1, & \text{if } (\cdot) < 0 \end{cases} \]

The norm of a matrix vector \( x \in \mathbb{R}^n \) is defined by

\[ ||x||^2 = x^T x. \]

**Definition 1:** Consider the nonlinear system

\[ \dot{x} = f(x, u, t), \quad y = h(x, t) \]

where \( x, u, \) and \( y \) are the vectors of states, inputs, and out-
puts, respectively. We say the solution is uniformly ultimately
bounded (UUB) if there exists a compact set \( U \) such that, for
all \( \forall x(t_0) = x_0 \in U \), there exists \( \varepsilon > 0 \) and a number \( T(\varepsilon, x_0) \)
such that \( ||x(t)|| < \varepsilon \) for all \( t \geq t_0 + T \) [31].

In the sequel, the minimum and maximum eigenvalues of
any matrix \( A = A^T > 0 \) are denoted by \( A_{\min} \) and \( A_{\max} \),
respectively.

A. Vehicle Dynamics
Prior to moving on to the model-based neurocontroller scheme,
a mathematical model is developed so that the controller may
e also be evaluated. The vehicle system used in the analysis is
a “Sevrin” (Mitsubishi Motors, Taiwan, R.O.C.) passenger
wagon, which is a front-wheel-driven and a front-wheel-steered
(FWS) system with 100/0 brake force distribution, as shown in
Fig. 2. The main assumptions made in deriving the model are
the following.

1) Roll, pitch, and bounce motions are negligible.
2) The effect of suspension on the tire axels is negligible.
3) Brake, throttle, and steering dynamics are discounted.

The first assumption is valid without appreciable loss in
accuracy under typical and slightly severe maneuvers for high-
way vehicles [15]. First, two assumptions that are common in
vehicle lateral motion control literature are assumed to be not
overly restrictive [12].

Fig. 1 shows three reference frames, namely 1) world fixed
frame \{W\}, 2) road reference frame \{R\}, and 3) vehicle frame
\{V\}. As bounce motion is not considered, all the reference
frames are assumed to be on the same horizontal plane. Since
only the position of the vehicle with respect to the road center-
line is relevant for lateral control, we are interested only in the
relative lateral position and velocity of the vehicle with respect
to the road frame \{R\}. To this end, \{R\}, which is on the road
centerline, is defined by an orthogonal basis \( e_r = [i_r, j_r]^T \) with
\( i_r \) on the tangent to the road centerline so that there is no relative