Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-3 (2016) 395–400

Integrating the effect of driver to improve handling performance of vehicle

Saeid Khosravani, Amir Khajepour, Barış Fidan *

* *Dept. of Mechanical and Mechatronics, University of Waterloo, Waterloo, Canada (e-mail:s4khosra,a.khajepour,fidan@uwaterloo.ca).*

Abstract: Considering the effect of human driver in the stability of vehicle has always been one of the most important nuances in vehicle literature. Yet, the lack of a standard framework for modeling the human behavior coerces the companies to mostly entrust to the drivers - as an unknown external input - for ultimate control tasks. This evinces that a key problem still to work out is a reliable control technique incorporating effect of human to serve driver's request better. In this paper a simple model of human path following behavior is used that capture the most important parameters of a driver as well as the cumulative driver's observation and the action delay. Integrating the driver model with a linear vehicle model, a linear parameter varying formulation is adopted. Assuming certain ranges for the parameters and their respective rate of changes, a controller robust to time delay is proposed and the corresponding disturbance attenuation in the sense of truncated ℓ_2 norm is estimated. From an implementation point of view, the important advantage of the proposed controller is that only uses the IMU sensor and the vehicle velocity estimation, without requiring extra information about the desired path. The control action is based on the current vehicle states along with the estimation of driver status. In distributed wheel drive implementation, an optimal torque distributor transfers the torque to the wheels to achieve the best overall performance. The simulation results show that the proposed technique improves the vehicle overall performance compared to the case that the controller is designed separately.

Keywords: Vehicle stability, Driver in the loop, Robust control, Linear Parameter varying, Time-delay systems.

1. INTRODUCTION

The ultimate goal of vehicle dynamic control can be defined as reducing the burden placed upon driver, i.e. increase safety level and ride comfort. Given that this aim depends on human and machine interaction; an interdisciplinary framework combining psychology, automotive engineering, computer science, control theory, etc. is needed to reach the goal. As a part of closed loop control system, the driver has to be considered in the design procedure. To formalize the problem, some researchers assume a relatively accurate model describing driver behavior while the driver's desired path (intention) is available for the vehicle controller. This way the controller has the road and environmental information as the reference signal along with the driver's inputs (seeShia et al. (2014)).
With current available technology, obtaining information about the driver's intentions on the desired path is not feasible. Although there is different proximity sensor, radars, and motion detectors available for implementation, the driver's intention is another level of information which needs very special tools to be obtained. This shortfall motivates us to seek methods that can improve the overall performance of a vehicle without having a prior knowledge on desired road paths. The control structure in Figure 1 is an implementable closed loop control structure that contains the driver model while the controller does not have any access to the driver's desired path (intention).
Since 1960, mathematical driver modeling and corresponding parameter identification techniques has become an active field of study (Lin et al. (2013), Mihaly and Gaspar (2014)). On the other hand, modeling uncertainty is inevitable in vehicle stability analysis, leading to use of robust control in this field. Considering recent progress in solving linear matrix inequality (LMI) problems, H_∞ methods are now more effective in handling deterministic disturbance models with bounded energy ℓ_2 signals (Kuzuya and Shin (2000)).
One of the most important methods for dealing with nonlinearity caused by tire saturation is linearized vehicle dynamics in different working points and using the model predictive control (MPC) method. This method predicts future vehicle states for a finite time horizon by using a plant model. The MPC method offers a control input that satisfies the plant constraints and minimizes a user defined cost function. Falcone et al. (2008) proposed a control scheme based on MPC to stabilize the vehicle in different scenarios such as obstacle avoidance, and the double-lane change maneuver.

One proper approach for tackling this problem is to combine the driver modeling and control problems more tightly by adding a model that predicts the driver behavior in prediction horizon. This way the MPC controller can use the predicted values to serve the driver better(see Carvalho et al. (2015), Di Cairano et al. (2014)).

10.1016/j.ifacol.2016.07.066

Recently, many researches have been devoted to robust stability analysis of LPV systems (Köroğlu (2014)). The problem of stability of time-delay LPV system has also been studied in several papers (Briat (2014), Pfifer and Seiler (2014)).
Drivers naturally need some time to observe and analyze a phenomenon before taking the action. This time varying delay can induce oscillation in the system and yields poor vehicle performance (see Khosravani et al. (2015), Chen and Ulsoy (2002), and Liu et al. (2004)). To counteract the effect of lag in the system, a control law robust to delay and uncertainties should be synthesized.
In this paper, using a general driver model, first a delayed LPV closed loop dynamic is formulated for the driver in the loop stability problem. Then, an LPV controller robust to modeling uncertainties and the delay is designed.

2. MODELING

2.1 Vehicle Modeling

The vehicle handling analysis is the main focus in this paper, hence a simplified bicycle model is considered as the main model.

$$ma_y = m(\dot{V}_y + V_x r) = F_{yr} + F_{yf}\cos\delta + F_{xf}\sin\delta \quad (1)$$
$$I\dot{r} = l_f F_{yf}\cos\delta - l_r F_{yr} + l_f F_f \sin\delta + M_z$$

Where I is the vehicle moment of inertia,δ is the steering angle, l_f and l_r are the distance from the centre of mass to the front and rear axle, F_{yf} and F_{yr} are the front and rear tire lateral force, F_{xf} is the longitudinal force of the front tire, M_z is the external moment, m is the vehicle's mass, V_x and V_y are the longitudinal and lateral velocity, r is the yaw rate, and a_y is the lateral acceleration.
Assuming that the vehicle steering wheel angle is small and the tire model is linear ($F_{yf} = C_f\alpha_f$) and $F_{yr} = C_r\alpha_{r)}$), the model can be represented by the following state space model:

$$\dot{x}(t) = Ax(t) + B_1\delta(t) + B_2 M_z(t) \quad (2)$$
$$x(t) = \begin{bmatrix} V_y & r \end{bmatrix}$$

$$A = \begin{bmatrix} \dfrac{-(C_f + C_r)}{V_x m} & \dfrac{-(l_f C_f - l_r C_r)}{V_x m} - V_x \\ \dfrac{-(l_f C_f - l_r C_r)}{V_x I} & \dfrac{-(l_f^2 C_f + l_r^2 C_r)}{V_x I} \end{bmatrix}$$

$$B_1 = \begin{bmatrix} \dfrac{C_f}{mG_s}, \dfrac{l_f C_f}{I_{Gs}} \end{bmatrix}^T \; B_2 = \begin{bmatrix} 0 & 1 \end{bmatrix}^T$$

where C_f and C_r are the front and rear tire cornering stiffness, α_f and α_r are the front (rear) tire slip angle, and G_s is the steering ratio between the hand wheel angle

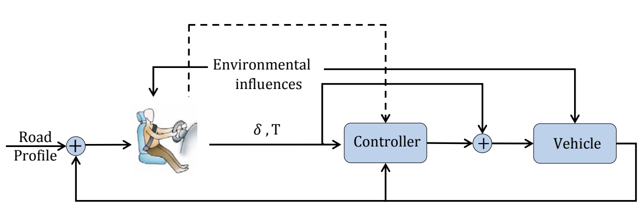

Fig. 1. Closed loop vehicle-driver control scheme

and the road wheel angle. There are two main sources of inaccuracy in the aforementioned model.
The first one is the tire nonlinear behaviour that the presented model cannot capture. The non-linearity of a tire is similar to saturation model that prevents the tire force to grow linearly with respect to tire slip angle. There are several techniques proposed for modelling this behaviour, however most of them are too complex to directly use in control design. Moreover, all these techniques require information about the road friction coefficient which is not easy to obtain. There are some papers presenting results of controller design robust to road coefficient changes, however mostly yielding in a conservative design which is not acceptable in real life application. Another approach is to assume that an estimation of the road friction information is available. Then a nonlinear or LPV controller can be casted respectively. For the sake of simplicity, in this paper we assume that the road friction is constant and known a prior. The extension of the model to LPV is possible by assuming the tire cornering stiffness is measurable or can be estimated.
The second limitation of the model in (2) is to consider a constant longitudinal velocity. Based on current technology, it is reasonable to assume that there exists a reliable estimation technique (using the stock IMU and the wheel speed sensor) or an accurate sensor such as GPS, to obtain the longitudinal velocity. In the rest of this paper, it is assumed that the longitudinal velocity is measurable at each sampling time, therefore the model in 2 can be represented in standard LPV form with known parameters.

2.2 Driver Path Following Model

There are various driver path-following models in the literature. The common factor of these models is that the steering wheel angle is a function of the desired future path (one or multiple preview point(s) in future) and the current vehicle states. Assuming that the driver's desired intention or path is available, the control design is an easier task of a decision making and authority allocation between machine and human. However, implementation of this idea still has several barriers as this information usually is not available for the controller even in semi-autonomous vehicles. Note that in semi-autonomous vehicles, the desired path might be available for the controller, however the desired intention of the driver is not accessible.
An alternative approach is to model a driver as a function of measurable (or observable) states of the vehicle and some unknown information related to the desired path. This approach enables the controller to extract some information from the driver model rather than considering the driver input as a bounded uncertainty.
Here we assume that the driver input can be represented as a follow:

$$\delta(t) = k_1 V_y(t) + k_2 r(t) + \omega(t) \quad (3)$$

where $\omega(t)$ is bounded uncertainty. Another important characteristic of human drivers is delay in action. From the time that a driver scans the environment until an action happens, a certain time elapses. The time variation and uncertainty in the amount of this delay also makes the system analysis more complicated.