Proceedings of the 14th
KACC, Octorber 1999

Observer Based Estimation of Driving Resistance Load for Vehicle Longitudinal Motion Control

°Duk Ho Kim*, Byung Kwan Shin*, Kyongsu Yi** and Kyo Il Lee*

* Dept. of Mech. Design and Prod. Eng., Seoul National University, Kwanak Ku, Seoul 151-742, KOREA
Tel : +82-2-880-7143; Fax : +82-2-883-1513; E-mail: dhkim2@snu.ac.kr
** School of Mechanical Engineering, Hanyang University, Seoul, 133-791, KOREA
Tel : +82-2-2290-0455; Fax : +82-2-2295-9970; E-mail: kyongsu@email.hanyang.ac.kr

Abstract

An estimation algorithm for vehicle driving load has been proposed in this paper. Driving load is an important factor in a vehicle's longitudinal motion control. An approach using an observer is introduced to estimate driving load based on inexpensive RPM sensors currently being used in production vehicles. Also, a torque estimation technique using nonlinear characteristic functions has been incorporated in this estimation algorithm. Using a nonlinear full vehicle simulation model, we study the effect of the driving load on longitudinal vehicle motion, and the performance of the estimation algorithm has been evaluated. The proposed estimation algorithm has good performance and robustness over uncertainties in the system parameters. An accurate estimate of the driving load can be very helpful in the development of advance vehicle control systems such as intelligent cruise control systems, CW/CA systems and smooth shift control systems.

1. Introduction

Recently, AVCS(Advanced Vehicle Control System) technology is being actively developed in automobile research areas. With regard to the realization of AVCS (Fig.1), difficulties lie mainly in the widely varying non-linear dynamic behavior of the vehicle and hard-to-measure signals. The longitudinal control system which provides safety and driving comfort is one of the most important examples of AVCS technology. In the many following applications related to vehicle longitudinal motion control, the driving resistance load has been recognized as an important factor limiting the control performance:

- intelligent cruise control system [1]
- collision warning and avoidance (CW/CA) system [2]
- powertrain shift logic control system [4]
- longitudinal vehicle platoon control [3]

Prior research has considered driving load on a running vehicle as external disturbances, and so performance absolutely depends on how robust the designed controller is over the driving load variation. In practice, the external load to a vehicle is costly to measure. Also, external load is a large and fast varying disturbance, since it comes from wind, the road envelope, etc. The vehicle's longitudinal motion control algorithms may greatly benefit if the driving load is available, and an estimation or adaptation of the driving load is necessary for improving the control performance.

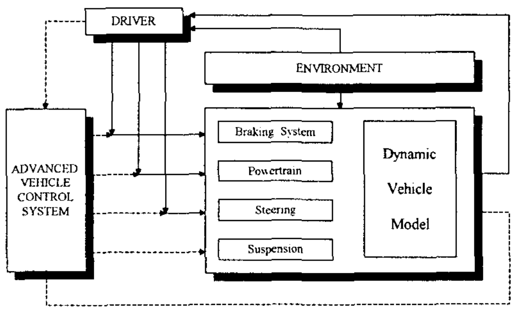


Fig. 1 Advanced Vehicle Control System

Hiroshi et al.(1998) proposed an estimation method using the simple kinetic method for application to avoiding shift change trouble when running uphill or downhill. However, this method may be more sensitive to variations in the system parameters and its performance may degrade under large variations in the road slope and abrupt changes in road conditions.

In this paper, we present an "observer-based" driving resistance load estimation method which can be implemented with information from easily-measurable states. Also, a torque estimation technique using nonlinear characteristic functions has been incorporated in this estimation algorithm. Using a nonlinear full vehicle simulation model, the effect of the driving load on longitudinal motion has been investigated and the performance of the estimation algorithm has been evaluated.

2. Driving Load Estimation

Figure 2 shows the estimation scheme using an observer, proposed in this study. The estimation algorithm can be divided into two parts: a linear observer design using rpm sensor measurements, and unknown input torque estimation. The Kalman filter has been designed for robustness under sensor noise and the error variance at steady state has been minimized.

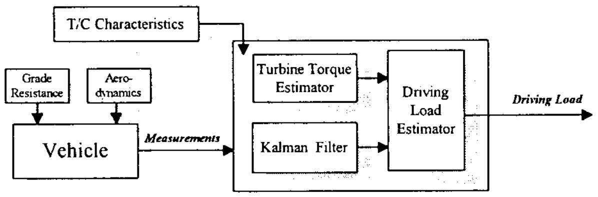


Fig. 2 Observer-based Driving Load Estimation Algorithm

For the driving load observer design, we use the subset of eight-state powertrain model developed by Cho and Hedrick (1989). This model has been used as the base model for many applications in vehicle longitudinal control and observer design.

The differential equation for the transmission carrier speed is:

$$\frac{d\omega_{cr}}{dt} = \frac{1}{I_{cr,i}}\left(\frac{T_t}{R_i} - R_d T_s\right) \tag{1}$$

The equation for the axle shaft torque dynamics is:

$$\frac{dT_s}{dt} = K_s(R_d\omega_{cr} - \omega_\omega) \tag{2}$$

The equation of motion for the wheel is written as follows:

$$\frac{d\omega_\omega}{dt} = \frac{1}{I_v}(T_s - T_L) \tag{3}$$

The embedded observer model which is introduced from the vehicle/transmission model is based on the following assumptions:

- The road surface condition is the same for all tires.
- The no-slip assumption has been incorporated because wheel slip is quite small at low levels of acceleration.
- The brake torque is neglected during throttle operation.

To design an observer, it is necessary to determine the measured states and inputs. For the embedded model, the driving load T_L in equation (3) is unknown, but can be estimated using inexpensive speed sensors currently in use on vehicles equipped with Anti-skid Braking (ABS) Systems. The driving load T_L can be considered as another state variable, and estimated by an observer. Since the observer period is rather short compared with the variation of T_L, the O-observer[7] is used in order to simplify the observer design in this study, assuming that

$$\frac{dT_L}{dt} = 0 \tag{4}$$

Augmenting the state vector with the driving resistance load,

$$x = [\omega_{cr}\ \omega_\omega\ T_s\ T_L]^T$$

together with the use of $u = T_t$ as the system input, leads to the state-space model :

$$\dot{x} = Ax + Bu\ , \qquad u = T_t\ (\text{ turbine torque })$$

With the measurements of transmission output speed and driven wheel speed i.e., $y = [\omega_{cr}\ \omega_\omega]^T$, observer design with pole placement is possible.

The problem is that the input to the observer is unknown and inaccessible. So, the input torque estimation for observer design is also required. This is shown in Section 3.

In the form of a linear estimator,

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + Bu + L(y - C\hat{x}) \\ y &= Cx + n\ , \end{aligned} \tag{5}$$

where

$$A = \begin{bmatrix} 0 & 0 & \frac{-R_d}{I_{cr,i}} & 0 \\ 0 & 0 & \frac{1}{I_v} & -\frac{1}{I_v} \\ K_sR_d & -K_s & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} \frac{1}{I_{cr,i}R_i} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Compared with the simple kinetic method,[8] the advantage of this approach using an observer is that the effects of sensor noise, disturbances acting on the vehicle and model uncertainties can be reduced by feedback signals. In addition, the dynamic estimate of the observer is accurate even during transients.

3. Torque Estimation

Torque is transferred to the turbine as a result of the oil induced flow from the pump which is attached directly to the engine. The pump torque T_p and turbine torque T_t are represented as follows:

$$\begin{aligned} T_p &= C_p(\omega_e, \omega_t)\,\omega_e^2 \\ T_t &= T_r(\omega_e, \omega_t)\,T_p \end{aligned} \tag{6}$$

The turbine torque, which is an unknown input to the observer, has been estimated using two nonlinear characteristic torque converter functions, as shown in Figure 3. Then the estimated turbine torque is incorporated as unknown input to the driving load estimation algorithm. In the case that the estimation error in torque is caused by the variation in the torque converter characteristicis, an adaptive torque estimation technique [6] can be used in the proposed estimation algorithm, instead of simply using two nonlinaer characteristic functions, so as to compensate for the variation in torque production.

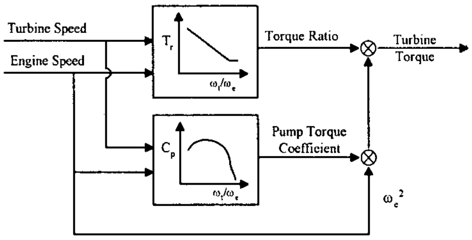


Fig. 3 Unknown Input Torque Estimation

4. Simulations and Discussion

In this section, we perform simulations to investigate the effect of the driving load on the longitudinal vehicle motion and evaluate the performance of the proposed estimation algorithm in many situations. As shown in figure 4, the powertrain models we use for simulation contains relevant dynamic characteristics of the engine/transmission and driveline of the vehicle based on a simple linear car model. The models we use here has been validated to be sufficiently able to capture the dynamic behavior of automotive powertrain systems.[5]

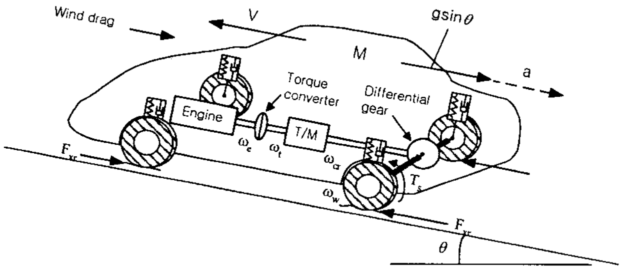
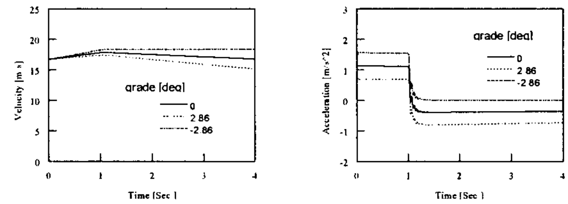


Fig. 4 Full Vehicle Model for Simulation

Many factors affect the magnitude of the driving resistance load: for example, the vehicle speed, road slope, road conditions, etc. In previous research works, it was shown that grade resistance force is the dominant factor and abrupt changes in the road slope contribute to large variations of the driving load, rather than the vehicle speed which is a slowly varying factor. The vehicle acceleration is used as the performance evaluation criteria in many AVCS technologies. So, the control laws using engine/brake torque should be designed to construct the optimal vehicle's acceleration profile so that both driveablility and safety may be obrained in vehicles' logitudinal control systems. We perform simulations to look at the acceleration profile of a car driving on different road grades. The results shown in figure 5 indicate the acceleration change with grade resistance of up to ± 1 m/s^2.



(a) Velocity (with grade) (b) Acceleration (with grade)

Fig. 5 Effect of Grade Load on Longitudinal Motion

Next, we evaluate the performance of the estimation algorithm with the following three cases based on the analysis of the driving load resistance.

4.1. CASE 1 : running on a road slope

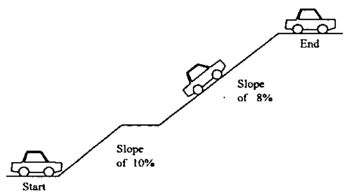


Fig. 6 Course Condition

Uphill driving simulation tests are performed to evaluate the estimation capability on the course condition shown in figure 6. Figure 7 shows that the proposed estimation scheme can provide quite an accurate estimate even during abrupt changes in the road slope.

4.2. CASE 2 : parametric uncertainties

Nonlinearities and uncertainties in the parameters are involved in the vehicle system. So, the estimation method applied to vehicle control systems should be robust against those uncertainties. We perform simulations to evaluate the observer's ability to handle uncertainties, such as vehicle inertia and axle shaft stiffness. Figure 8 shows the estimation performance on running on a road slope under 30 % uncertainty of axle shaft stiffness, and the dynamic estimate of an observer is accurate even during transients.

4.3. CASE 3 : changes in road conditions

The driving load for different road conditions, for example, concrete, medium hard and sand, varies widely. Figure 9 shows the estimation performance for

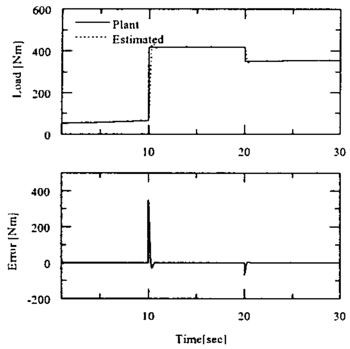


Fig. 7 Estimation Performance on a Varying Road Slope

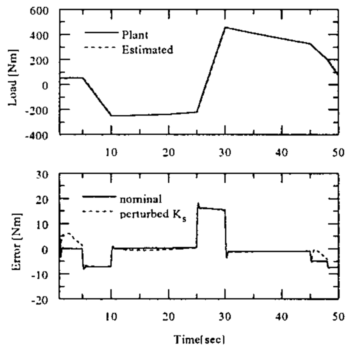


Fig. 8 Estimation Performance with an Uncertain Parameter : Ks

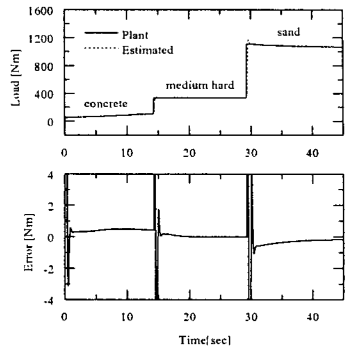


Fig. 9 Estimation Performance under Changes in Road Conditions

abrupt changes in rolling resistance due to widely varying road conditions. The simulation result indicates that the observer shows good performance in accurately estimating driving load for widely varying road conditions.

5. Conclusion

In this paper, an approach using an observer is introduced to estimate the driving load based on inexpensive rpm sensors currently being used in production vehicles. The torque estimation technique using nonlinear characteristic functions has also been incorporated in this estimation algorithm. The effectiveness of the observer-based method is demonstrated through the use of a full vehicle simulation in various situations. We also study the effect of the driving load on longitudinal vehicle motion. The proposed estimation algorithm has good performance and robustness over uncertainties in the system parameters. The driving load estimation is quite accurate even during large variation on a road slope and abrupt changes in the road conditions. An accurate estimate of the driving load can be very helpful for vehicle longitudinal motion control systems, such as the intelligent cruise control system, the CW/CA system and the powertrain shift logic control system. For integration with AVCS technology, future work will require experimental implementation of the observer.

Appendix

List of symbols

T_L : driving load torque $\quad$ K_s : axle shaft stiffness

I_v : vehicle inertia $\quad$ $I_{cr,i}$: carrier inertia

T_s : axle shaft torque $\quad$ T_t : turbine torque

ω_ω : wheel speed $\quad$ ω_{cr} : carrier speed

R_i : speed ratio $\quad$ R_d : final speed reduction ratio

Acknowledgement

This work was supported (in part) by the Korea Science and Engineering Foundation (KOSEF) through the Torbo and Power Machinery Research Center at Seoul National University.

References

[1] M.K. Liubakka et al., "Adaptive Automotive Speed Control", IEEE Trans. Automatic Control, 38: pp. 1011-1020, 1993

[2] Yi.K. and Jeong,T., "Development of a Simulator and Control Program for Vehicle Distance Warning Systems", VDCL Report #97-4, 1997

[3] J.K. Hedrick et. al., "Longitudinal Control Development for IVHS Fully Automated and Semi-Automatic Systems-Phase 1", California PATH Research Report, 1995

[4] Hayashi et al., "Neuro Fuzzy Transmission Control for Automobile with Variable Loads", IEEE Trans. Control System Technology, Vol.3, No.1, pp. 49-53, 1995

[5] D.Cho, and J.K. Hedrick, "Automotive Powertrain Modeling for Control", ASME Journal of Dynamic Systems, Measurement and Control, Vol. 111, No 4, pp. 568-576, 1989

[6] K.S Yi, B.K. Shin, K.I. Lee., "Estimation of Turbine Torque using an Adaptive Nonlinear Observer for Closed-Loop Control of Vehicle Automatic Transmisions", submitted for publication

[7] Meditch, J.S. and G.H. Hostetter, "Observers for systems with unknown and inaccessible inputs", International Journal of Control, Vol.19, No.3, pp.473-480

[8] Hiroshi et al., A Study of Road Slope Estimation on Running Vehicles with Automatic Transmission, AVEC'98, pp.177-182