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Improving the e-Pedal performance during towing by estimating the vehicle mass

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Executive Summary

The e-Pedal can completely stop a vehicle by releasing only the accelerator pedal, even on a slope. In this paper, we present the incorporation of a vehicle mass estimating function to the e-Pedal control. It compensates for the e-Pedal control constants and prevents the vehicle from failing to stop at the target position or moving backward when the vehicle mass increases significantly owing to cargo or towing. For vehicle mass estimation, an extended Kalman filter is applied using the acceleration sensor signals as an input, as well as an estimation method that can eliminate the influence of gradient variables. Finally, we demonstrate the proposed method via experiments conducted on actual vehicles.

Keywords: electric vehicle (EV), control system, regenerative braking, modeling, heavy-duty

1 Introduction

Battery electric vehicles (BEVs) have been rapidly gaining market share for over ten years because of their outstanding environmental performance, including lower fossil fuel use, CO_2 emissions, and air pollution compared to conventional vehicles. Although most BEVs were initially launched as passenger vehicles, they have recently been marketed as various vehicle types, ranging from commercial vans and buses to full-size pickups.

BEVs have advantages not only from an environmental perspective but also in their highly responsive acceleration performance and high level of silence owing to their motor drive system, with additional functions utilizing the controllability of motors being developed [1] [2]. One of these functions is the e-Pedal, which uses the regenerative torque of the drive motor to decelerate and stop a vehicle without using a brake pedal [3]. This enables a vehicle to smoothly reach a complete stop, even on a slope, simply by releasing the accelerator pedal. This function liberates the driver from the hassle of frequent switching between accelerator and brake pedals and improves the value of BEVs through control in addition to their environmental performance.

Because e-Pedal were developed for passenger vehicles, the change in the vehicle mass, which affects the stop control performance, is less than approximately 20% of the mass of the vehicle itself. However, a significant increase in mass, as in the case of cargo or towing vehicles, may prevent the vehicle from coming to a smooth stop.

The purpose of this study was to demonstrate the consistency of the e-Pedal performance for vehicles with a possible significant increase in mass, as in the case of cargo or towing vehicles. For this purpose, mass estimation logic is developed to counter the problem, and its effectiveness is verified by performing experiments on actual vehicles.

2 e-Pedal control

2.1 Control strategy

e-Pedal, which is a technology based on the regenerative torque of the motor, enables the driver to slow down and stop a vehicle using only the accelerator pedal, regardless of the road grade. Reducing the frequency of brake operations reduces a driver's physical workload and lowers the electric power consumption required for driving. Figure 1 shows three functions required of e-Pedal.

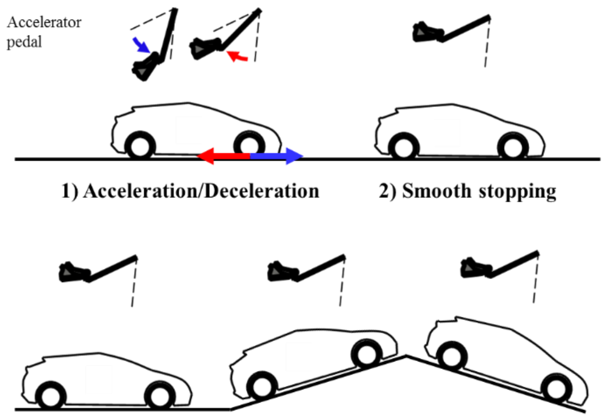

Figure 1: Required functions for e-Pedal

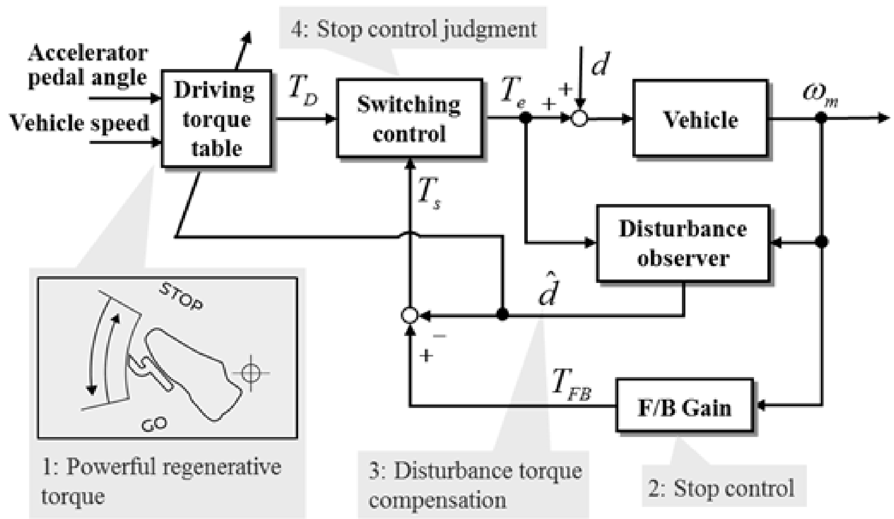

Figure 2: Function block diagram of e-Pedal control

A function block diagram of the e-Pedal control system designed to achieve these functions is shown in Figure 2.

1) Acceleration/deceleration

This function was accomplished by calculating the driving torque command from the driving torque table. This generates a powerful regenerative torque when the accelerator pedal angle is small.

2) Smooth stopping

Smooth stopping was achieved by feedback control of the motor speed. The feedback gain was designed theoretically to ensure the stability of the feedback control system to smoothly stop the vehicle.

3) Deceleration and stopping regardless of the road grade

The disturbance observer estimates a disturbance torque value that is equal to the torque required to stop on a particular road grade.

The e-Pedal control torque command T_e is selected by switching the control block that determines the stop control operating conditions based on the driving torque command T_D and the stop control torque T_s.

2.2 Disturbance observer

The block diagram of the disturbance observer is shown in Figure 3.

The disturbance observer estimates the disturbance $\hat{d}$ based on the deviation between the actual motor speed ω_m and $\hat{\omega}_m$, which is calculated using the reference response $G_r(s)$ of the vehicle when T_e is input. Because $G_r(s)$ is the reference response designed based on $G_p(s)$, vehicle mass M is used as a parameter. $H(s)$ is a filter that adjusts the response of the disturbance observer.

These transfer functions are described below.

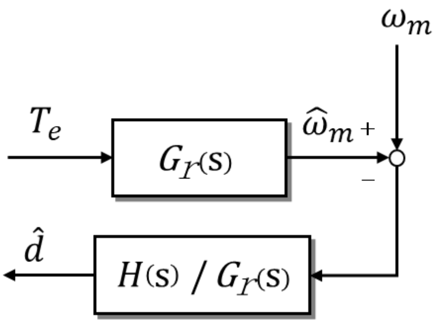

Figure 3: Block diagram of the disturbance observer

Figure 4 and Figure 5 show the models of the drive-torque transmission system and the forward/backward motion of the vehicle body. The equations of motion for the vehicle represented in Figure 4 and Figure 5 are expressed as shown in Equation (1).

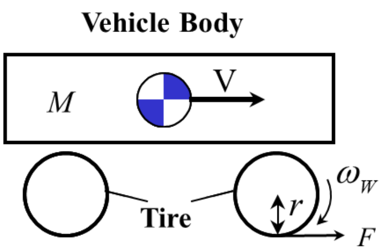

Figure 4: Forward and back movement model of vehicle

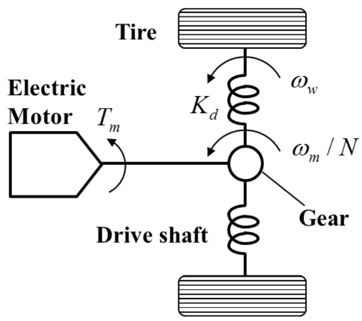

Figure 5: Driving torque transmission model

$$J_m \frac{d}{dt}\omega_m = T_m - \frac{T_d}{N}$$

$$2J_w \frac{d}{dt}\omega_w = T_d - rF$$

$$M\frac{d}{dt}V = F \quad (1)$$

$$T_d = K_d \int \left(\frac{\omega_m}{N} - \omega_w\right) dt$$

$$F = K_t(r\omega_w - V)$$

J_m	: motor inertia	T_m	: motor torque
J_w	: drive wheel inertia	T_d	: drive shaft torque
M	: vehicle mass	F	: driving force
K_d	: torsional stiffness of drive shaft	N	: overall gear ratio
r	: radius of tire load	K_t	: tire constant
ω_w	: wheel speed	V	: vehicle velocity
ω_m	: motor speed		

Based on Equation (1), the transfer function $G_p(s)$ with motor torque as the input and the motor speed as the output is obtained by Equation (2).

$$\omega_m = G_p(s)\, T_m \quad (2)$$

The disturbance observer was configured based on the assumption that the control was designed to suppress the torsional vibration of the drive shaft. Details may be found in a prior study [1]. The transfer function $G_c(s)$ of the torsional vibration suppression controller provides a response as $G_r(s)$. The function of this controller is to reduce the damping coefficient of torsional vibration.

$$\hat{\omega}_m = G_r(s)\, T_e$$

$$T_m = G_c(s)\, T_e \quad (3)$$

$$G_c(s) = \frac{G_r(s)}{G_p(s)}$$

2.3 Effect of change in mass

As shown above, the disturbance observer estimates the variation in the motor speed ω_m and reference response $\hat{\omega}_m$ corresponding to the input torque T_e as a disturbance, estimating it as a disturbance torque when the vehicle mass changes as well. For example, when traveling on a flat road with an increase in vehicle mass, it estimates the gradient resistance as high during acceleration, as if the vehicle was traveling uphill, and it estimates the resistance as negative during deceleration, as if traveling downhill, and as a disturbance. In contrast, when traveling at a constant speed on a flat road, the mass has no effect when the vehicle motion includes a stop or has no deceleration. Therefore, the disturbance decreases as the deceleration decreases in the situation where the vehicle is decelerating to a stop with e-Pedal; subsequently, the disturbance reduces to zero when the vehicle stops. However, because the disturbance observer has a delayed response, the compensation by the estimated disturbance torque remains at the moment of a stop by the stop control, causing to move backward.

Figure 6 shows the simulation during the stop control at various masses. When the mass change is large, the motor rotates in reverse after stopping, causing the vehicle to move backward.

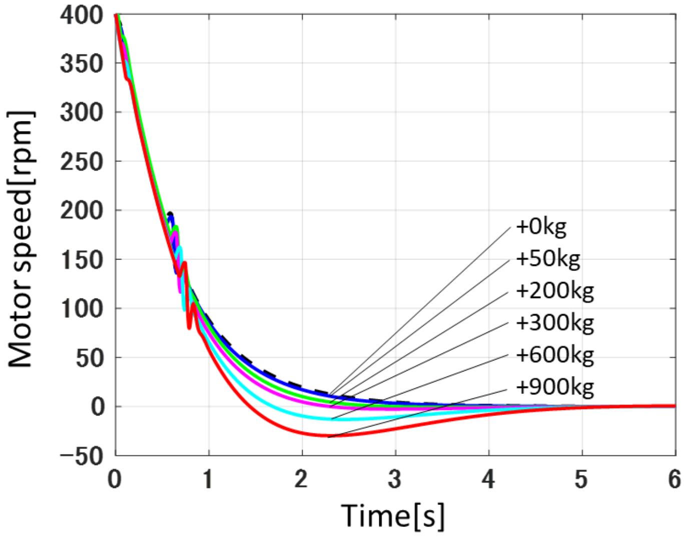

Figure 6: The simulation during the stop control at various masses

3 e-Pedal control with Vehicle mass estimation

3.1 Control block diagram

The control block diagram of the e-Pedal control embedded with additional vehicle mass estimation is shown here. The configuration is designed to adjust the vehicle mass parameters of the disturbance observer using the vehicle mass estimation value estimated by the vehicle mass estimation.

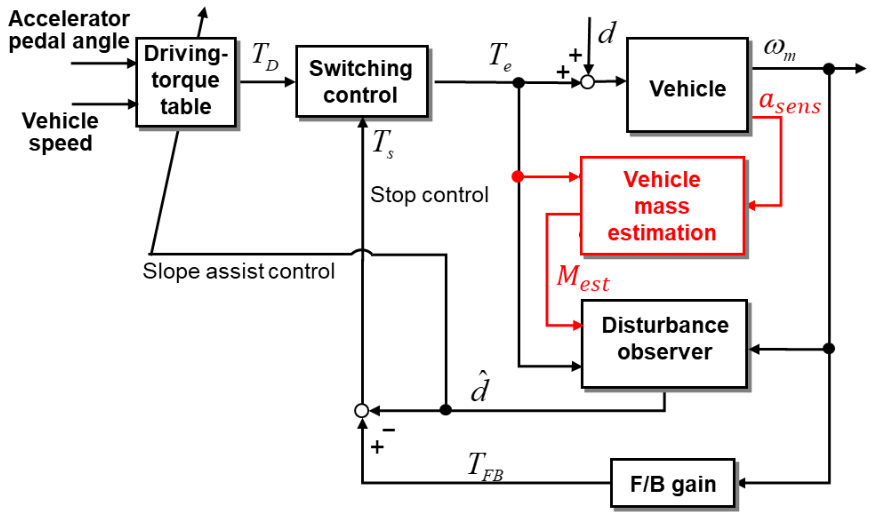

Figure 7: Vehicle mass estimation based on extended Kalman filter algorithm

3.2 Vehicle mass estimation based on extended Kalman filter algorithm

The conventional method of vehicle parameter estimation often used vehicle speed as an input to simultaneously measure vehicle mass and road grade [4]. The disturbance observer dynamically compensates for the road grade in the e-Pedal stop control, eliminating the need to estimate the road grade and leaving only the vehicle mass to be estimated. Therefore, this method eliminates the road grade from the estimation parameters using an acceleration sensor for the input signal. The aim is to make the estimation easier by reducing the number of unknown parameters. An extended Kalman filter is used for the estimation logic. The following describes the algorithm for estimating the vehicle mass using acceleration sensor values.

3.2.1 Modeling

Here, the acceleration of the vehicle is modeled. The driving force is calculated from the motor torque by considering the rotational acceleration of the drive-train inertia. The driving resistance consists of a rolling resistance and air resistance.

$$\begin{aligned} M\dot{v} &= F_d - F_g - F_r - F_a \\ F_d &= \frac{N}{r}(T_e - J_a\dot{\omega}_m) \end{aligned} \tag{4}$$

M	: Trailer and vehicle mass	$\dot{v}$	: Vehicle acceleration
F_d	: Driving force by motor	F_g	: Gradient resistance
F_r	: Rolling resistance	F_a	: Air resistance
J_a	: Sum of drive-train inertias on motor side	r	: Radius of tire
ω_m	: Motor speed	N	: All over gear ratio

The acceleration sensor outputs not only the acceleration of the vehicle but also the gravitational acceleration caused by the road grade as a sensor value; thus, the acceleration sensor value a is expressed in Equation (5). The driving inputs to the vehicle, except for the gradient resistance, are summed up in u, as shown in Equation (6), and the vehicle model is given in Equation (7).

$$a = \dot{v} + \frac{F_g}{M} \tag{5}$$

$$u = F_d - F_r - F_a \tag{6}$$

$$a = \frac{1}{M}u \tag{7}$$

3.2.2 State space model

Here, the state space for the Kalman filter is modeled. To estimate the vehicle mass, the acceleration sensor value a, modeling error e, and vehicle mass M are chosen as state variables. Persistent prediction is applied for modeling error e and vehicle mass M. The driving force u is given by Equation (6), considering the running resistance which is calculated based on the motor torque.

Accordingly, the state equation and observation equation are given by Equations (8) and (9), respectively.

$$x_{k+1} = \begin{bmatrix} a_{k+1} \\ e_{k+1} \\ M_{k+1} \end{bmatrix} = \begin{bmatrix} \frac{1}{M_k} u_k + e_k \\ e_k \\ M_k \end{bmatrix} + \begin{bmatrix} w_k^a \\ w_k^e \\ w_k^M \end{bmatrix} = f(x_k, u_k) + w_k \tag{8}$$

$$y_k = H_k \begin{bmatrix} a_k \\ e_k \\ M_k \end{bmatrix} + v_k \tag{9}$$

w_k and v_k are noises, which are assumed to have a mean of 0 and a normal distribution with covariance matrices Q_k and R_k, respectively.

Because the observation equation maps the state space to the observation space, H_k can be expressed by Equation (10) as follows.

$$H_k = [1 \quad 0 \quad 0] \tag{10}$$

3.2.3 Linear approximation

$f(x_k, u_k)$ is a nonlinear function, which is approximated as a linear function using a Jacobian matrix. Equation (11) is defined as follows:

$$f(\hat{x}_{k-1}, u_k) = \begin{bmatrix} f_a \\ f_e \\ f_M \end{bmatrix} \tag{11}$$

The Jacobian can be calculated using Equation (12).

$$F_k = \left.\frac{\partial f}{\partial x}\right|_{\hat{x}_{k-1|k-1}, u_k} = \begin{bmatrix} \frac{\partial f_a}{\partial a} & \frac{\partial f_a}{\partial e} & \frac{\partial f_a}{\partial M} \\ \frac{\partial f_e}{\partial a} & \frac{\partial f_e}{\partial e} & \frac{\partial f_e}{\partial M} \\ \frac{\partial f_M}{\partial a} & \frac{\partial f_M}{\partial e} & \frac{\partial f_M}{\partial M} \end{bmatrix} = \begin{bmatrix} 0 & 1 & -\frac{u_k}{M_k^2} \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{12}$$

3.2.4 Extended Kalman filter

Figure 8 depicts the block diagram of the extended Kalman filter in this method with the algorithm described below.

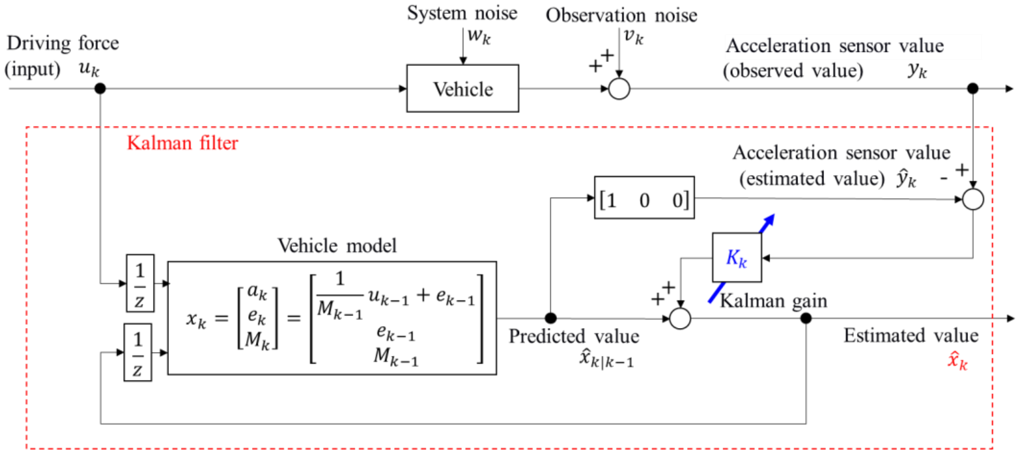

Figure 8: Mass estimation by extended Kalman filter

Prediction step

The prior state estimate is predicted using the previous state estimate and the state equation.

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k) \tag{13}$$

The prior error covariance matrix is calculated as follows.

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \tag{14}$$

Filtering step

The Kalman gain is calculated as follows.

$$K_k = \frac{P_{k|k-1} H_k^T}{H_k P_{k|k-1} H_k^T + R_k} \tag{15}$$

Then, the state estimate is calculated using the formula below.

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - H_k \hat{x}_{k|k-1}) \tag{16}$$

The posterior error covariance matrix is calculated as follows:

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{17}$$

Where P is the error covariance matrix, K is the Kalman gain. Q_k and R_k are the covariance matrix for the process noise and observed noise, respectively.

The larger the covariance, the greater the error included during the state transitions and observations. Here, because a, e, and M are independent of each other and autocovariance (diagonal components of the covariance matrix) is important among the covariances, Q_k and R_k are given as follows:

$$Q_k = \begin{bmatrix} q_a & 0 & 0 \\ 0 & q_e & 0 \\ 0 & 0 & q_M \end{bmatrix} \tag{18}$$

$$R_k = r_a$$

q_a, q_e, q_M, and r_a are the autocovariances of a, e, and M, respectively. Q_k is the sampling rate, and R_k depends on the noise characteristics of the sensor and is experimentally tuned.

Initial values were set as follows:

$$x_0 = \begin{bmatrix} 0 \\ 0 \\ M_{ref} \end{bmatrix} \tag{19}$$

$$P_0 = Q_k$$

where M_{ref} is the nominal value of the vehicle mass.

4 Vehicle test results

4.1 Vehicle mass estimation

The estimated results when the number of passengers increased by one per lap of a course are shown in Figure 9. The estimation results were good.

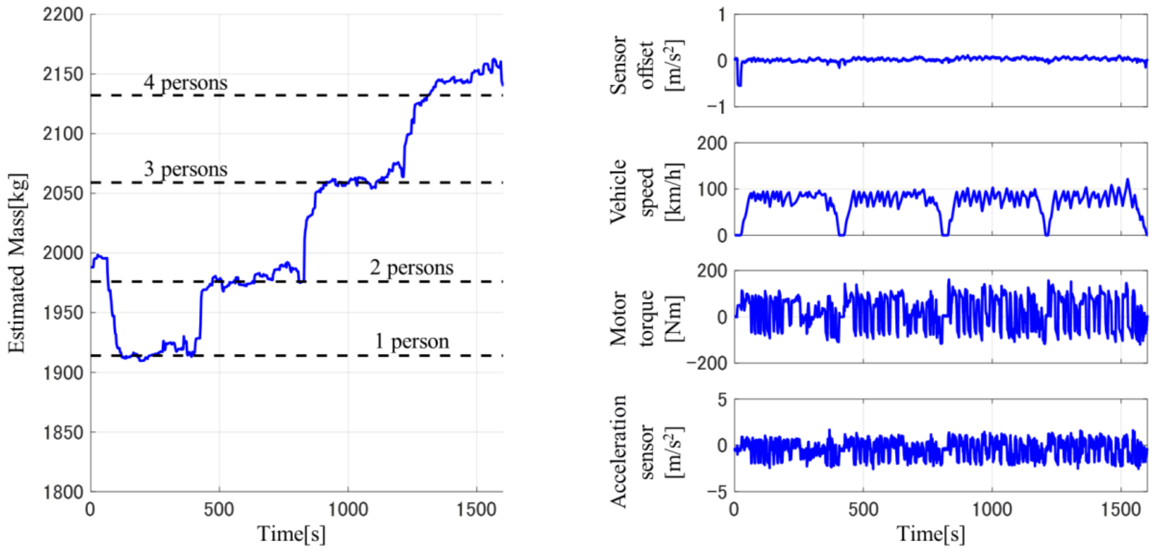

Figure 9: Vehicle mass estimation test results

4.2 e-Pedal system using vehicle mass estimation

A test vehicle experiment was carried out to confirm the usefulness of the proposed method. The test condition defined for e-Pedal is that an EV with an increased mass of 900 kg is used by towing a trailer, and the vehicle decelerates to a stop when the accelerator pedal is released at a constant vehicle speed on an uphill slope. The test results are shown in Figure 10.

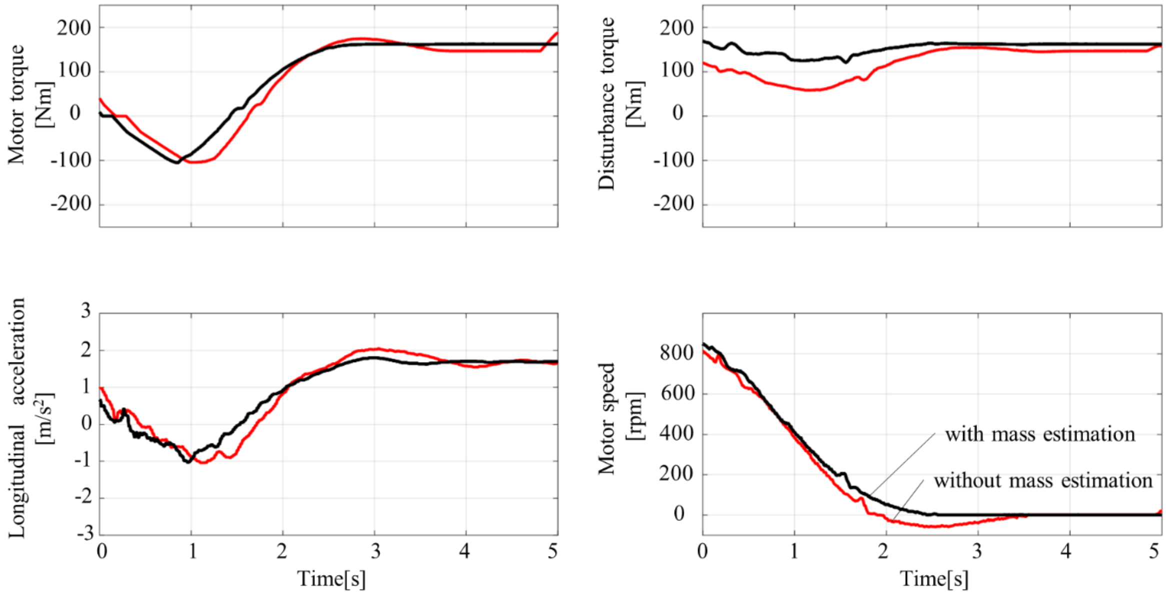

Figure 10: Experimental results for stop control

The red lines represent the results without the vehicle mass estimation. The vehicle rolls back before stopping. In contrast, the black lines represent the results of vehicle mass estimation, which allowed the vehicle to stop without rolling back.

The upper-right graph shows the disturbance estimates. The disturbance estimates change less with vehicle mass estimation than without it. This indicates that the mass change is no longer estimated as a road grade by reflecting the estimated mass in the parameters of the disturbance observer, which confirms the targeted operation of this method.

Consequently, compensating for the parameters of the disturbance observer of the e-Pedal control using the mass estimation method shown in Chapter 3 enables the separation of the mass effect from the disturbance estimate during vehicle acceleration and deceleration, as well as the extraction of the gradient disturbance depending on the road grade during driving, even when there is a significant change in mass.

5 Conclusion

- The mass estimation function was incorporated in this function to solve the problem wherein the stop control performance of e-Pedal deteriorates when there is a significant change in vehicle mass, as in the case of towing.
- An extended Kalman filter was employed for mass estimation to compensate for the mass parameters of the disturbance observer of the e-Pedal control.
- The extended Kalman filter was configured to use the motor torque and acceleration sensor as inputs to eliminate the influence of the road grade.
- Using the estimated mass prevents moving backward when towing.

While mass estimation was utilized for the e-Pedal stop control in this study, it may also be utilized for other vehicle motion control as well as BEV and hybrid electric vehicle energy management.

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Presenter Biography

Kengo Fujiwara received the B.Sc. and M.Sc. degrees, both in Mechanical Engineering, from Kansai University, Japan, in 1997 and 1999, respectively.

1999–2017, Engineer of electric motor control, Nissan Motor Corporation.

2017–present, Senior Manager of electric motor control, involved in developing the electric powertrain of the new Nissan BEV and e-POWER.