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Fault Diagnosis Algorithm for Driving Motor of In-Wheel Independent Drive Electric Vehicle

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Abstract **-**This paper presents a fault diagnosis algorithm for driving motor of In-wheel independent drive electric vehicle using vehicle dynamic analysis. The driving motor fault is detected and isolated based on the residuals. The residuals are provided with the wheel dynamics. The wheel dynamics are composed of a motor driving torque, wheel speed and longitudinal force. The longitudinal force estimated by analyse a planar two track model and a nonlinear simple tire model. The proposed fault diagnosis algorithm is verified by CarSim® and Matlab/Simulink® cosimulation.

***Keywords*:** In-wheel Independent drive electric vehicle, Fault diagnosis, Planar two track nonlinear model, nonlinear simple tire model, Residual, Redundancy

1. Introduction

Eco friendly cars, such as fuel cell vehicles and electric vehicles, have been actively studied worldwide in the recent years to solve environmental and energy problems. Out of these, In-wheel independent drive electric vehicle mounting the drive motor in the each wheel has attracted attention for reasons such as improving system efficiency and performance of vehicle stability control as shown by Yoichi et al. (1998, 2004). However, the drive motor mounted in the each wheel will be exposed to harsh environments such as physical shock or rapid temperature and humidity changes. This may have resulted in a frequent failure. For the safety of the vehicle, fault diagnosis of the drive motor are important issues.

There are two kinds of solutions in fault diagnosis. The first solution is hardware redundancy which adds another actuators or sensor as an extra hard ware. It is a physically simple method but additional cost is required. The second one is analytical redundancy which used mathematical model. In the car, the analytical redundancy is commonly used because this does not need any additional costs. This study proposes a fault diagnosis using the analytical redundancy.

There are numerous study results about fault diagnosis for the drive motor of the vehicle. The sensorless control algorithm is used for the rotor angle estimation to detect a fault of the motor position sensors, and if the difference between the measured angle and the estimated one is larger than a threshold value, then the control algorithm should be reconfigured to the sensorless control as shown by Benbouzid et al. (2007) and Demba et al. (2004). There was a study of the improvement of reliability through the optimal IPM motor design of the proper number of slots, winding distribution, and increasing number of phases as shown by Leila et al. (2007). Other studies focused on the faults of power semiconductors of an inverter and stator windings of a motor as shown by Ahmed et al. (1993) and Brian et al. (2002). Another studies are current sensor fault diagnosis through the additional circuit as shown by Yu-seok et al. (2005) and the current frequency analysis as shown by Bilal et al. (2009) when the vehicle is stop.

So most of fault diagnosis of the drive motor have been mainly performed at the low-level system not the vehicle dynamics but the subcomponent such as motor and inverter. Fault diagnosis of the low-level system is suitable for the sensor fault, but is difficult for actuator fault since it is difficult to know load torque transmitted from the outside of the vehicle. Moreover, fault diagnosis of the subcomponent is sensitive to noise and system uncertainties can be a fault alarm as shown by Xiaowen et al. (1994) and B. Song et al. (2005). So there is need of additional fault diagnosis of the high-level to enhance the robustness as shown by Soontae et al. (2008). This paper presents a fault diagnosis algorithm of the high-level for driving motor of In-wheel independent drive electric vehicle using vehicle dynamic analysis.

The driving motor fault is detected and isolated based on the residuals. The residuals are provided with the wheel dynamics. The wheel dynamics are composed of a motor driving torque, wheel speed and longitudinal force. The longitudinal force estimated by analyse a planar two track model and a nonlinear simple tire model. The proposed fault diagnosis algorithm is verified by CarSim® and Matlab/Simulink® cosimulation.

Nomenclature

m	Vehicle mass
m_s	Vehicle sprung mass
$l\ l_{f,r}$	Wheel base
$l_{f,r}$	Distance between mass center and axle
h_s	Sprung mass height
$t_{f,r}$	Vehicle tread
a_x	Longitudinal acceleration
a_y	Lateral acceleration
k_f	Lateral weight-shift distribution on the front wheel
k_r	Lateral weight-shift distribution on the rear wheel

Subscripts

fl, FL	Front left
fr, FR	Front right
rl, RL	Rear left
rr, RR	Rear right

2. Vehicle Model

A plane two track model is considered to represent the each wheel longitudinal and lateral forces for fault diagnosis of each wheel drive motor.

2. 1. Plane Two Track Model

Fig. 1. Shows the plane two track model including each wheel longitudinal and lateral forces. The longitudinal, lateral and yaw dynamics model of the vehicle is described as follows:

$$\dot{v}_x = \dot{\psi} \cdot v_y + \frac{1}{m}\left\{\left(F_{xfl} + F_{xfr}\right)\cos\delta_f + \left(F_{yfl} + F_{yfr}\right)\sin\delta_f + \left(F_{xrl} + F_{xrr}\right)\right\} \tag{1}$$

$$\dot{v}_y = -\dot{\psi} \cdot v_x + \frac{1}{m}\left\{\left(F_{xfl} + F_{xfr}\right)\sin\delta_f + \left(F_{yfl} + F_{yfr}\right)\cos\delta_f + \left(F_{yrl} + F_{yrr}\right)\right\} \tag{2}$$

$$\begin{aligned} I_z\ddot{\psi} &= l_f\left\{\left(F_{yfl} + F_{yfr}\right)\cos\delta_f + \left(F_{xfl} + F_{xfr}\right)\sin\delta_f\right\} - l_r\left(F_{yrl} + F_{yrr}\right) \\ &\quad + w_f\left\{\left(F_{yfl} - F_{yfr}\right)\sin\delta_f + \left(-F_{xfl} + F_{xfr}\right)\cos\delta_f\right\} + w_r\left(-F_{xrl} + F_{xrr}\right) \end{aligned} \tag{3}$$

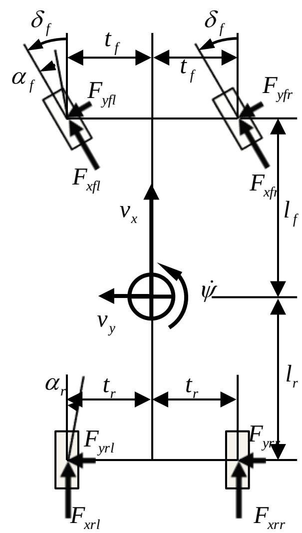

Fig. 1. Plane two track model

2. 2. Nonlinear Simple Tire Model

The nonlinear simple tire model is used for calculating the longitudinal and lateral tire forces. This model is easy to tuning and replicate similar to the actual in linear and nonlinear range. The nonlinear simple tire model is implemented using the hyperbolic tangent, and the equations are as follow.

$$F_x = k_x F_z \tanh\left(\varepsilon_x \kappa\right) \tag{4}$$

$$F_x = k_x F_z \tanh\left(\varepsilon_y \alpha\right) \tag{5}$$

where $k_{x,y}$, $\varepsilon_{x,y}$ are the tuning factors, κ is the tire slip ratio, and α is the tire slip angle.

The tire slip ratio and the tire slip angle equations are as follow.

$$\kappa_{fl} = \frac{r\omega_{fl}}{v_x - t_f\dot{\psi}} - 1, \kappa_{fr} = \frac{r\omega_{fl}}{v_x + t_f\dot{\psi}} - 1, \kappa_{rl} = \frac{r\omega_{fl}}{v_x - t_r\dot{\psi}} - 1, \kappa_{rr} = \frac{r\omega_{fl}}{v_x + t_r\dot{\psi}} - 1 \tag{6}$$

$$\alpha_{fl} = \delta_f - \frac{v_y + l_f\dot{\psi}}{v_x - t_f\dot{\psi}}, \alpha_{fr} = \delta_f - \frac{v_y + l_f\dot{\psi}}{v_x + t_f\dot{\psi}}, \alpha_{rl} = \delta_r - \frac{v_y - l_r\dot{\psi}}{v_x - t_r\dot{\psi}}, \alpha_{rr} = \delta_r - \frac{v_y - l_r\dot{\psi}}{v_x + t_r\dot{\psi}} \tag{7}$$

Considering the effect of weigh shift due to both roll and pitch, equations of vertical forces can be obtained by the following equations assuming that vehicle longitudinal and lateral accelerations are measured as shown by Ossama et al. (2008).

$$F_{zfl} = \frac{mgl_r}{2l} - \frac{m_s a_x h_s}{2l} - k_f \frac{m_s a_y h_s}{t_f}, F_{zfr} = \frac{mgl_r}{2l} - \frac{m_s a_x h_s}{2l} + k_f \frac{m_s a_y h_s}{t_f},$$
$$F_{zrl} = \frac{mgl_f}{2l} + \frac{m_s a_x h_s}{2l} - k_r \frac{m_s a_y h_s}{t_r}, F_{zrr} = \frac{mgl_f}{2l} + \frac{m_s a_x h_s}{2l} + k_r \frac{m_s a_y h_s}{t_r} \quad (8)$$

Fig. 2. Shows a comparison of a simple tire model with the Carsim tire model.

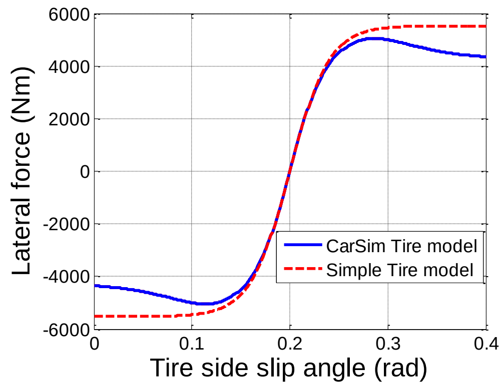

Fig. 2. Comparison of a simple tire model with the Carsim tire model

2. 3. Wheel Dynamics

The wheel dynamics can be written as follows by using the each wheel speed and the motor driving torque:

$$\dot{\omega}_{wi} = \frac{1}{I_\omega}\left(T_{mi} - r_{eff} F_{xi} - M_{yrri}\right), i = fl, fr, rl, rr \quad (9)$$

where ω_w is the wheel speed, T_m is the motor driving torque, M_{yrr} is the rolling resistance, r_{eff} is the effective rolling radius, and I_ω is the tire moment of inertia.

3. Fault Diagnosis Algorithm

This study derives the correlation between each sensor and Residual by analysis how the fault of the drive motor affect the entire vehicle.

3. 1. Residual

The wheel dynamic can be expressed as the residual. In the absence of the drive motor fault, the residual is near '0'. The residual equations are as follows.

$$r_i : 0 = \frac{1}{I_\omega}\left(T_{mi} - r_{eff} F_{xi} - M_{yrri}\right), i = fl, fr, rl, rr \quad (10)$$

M_{yrri} can be ignored by an adaptive residual threshold under the assumption that small when the motor is driven.

3. 2. Estimation Of The Longitudinal Forces

From Eq. (10), it is clear that estimation of the longitudinal forces is essential to be used in the fault diagnosis. The longitudinal forces calculation using Eq. (4) is not accurate since the tuning factor k_x is different for each road surface. Therefore a model observer is used for the longitudinal forces estimation process. This observer used Eq. (1) and Eq. (4) under the assumption that the sign of the longitudinal slips of the each wheel is the same and the longitudinal forces is assumed to be larger than the lateral forces. The longitudinal dynamics equation ignoring the lateral force is as follows.

$$F_{x,total} = \left(F_{xfl} + F_{xfr}\right)\cos\delta_f + \left(F_{xrl} + F_{xrr}\right) = m\left(\dot{v}_x - \dot{\psi}\cdot v_y\right) \tag{11}$$

From Eq. (4) and (11), $F_{x,total}$ is described by the following equation.

$$m\left(\dot{v}_x - \dot{\psi}\cdot v_y\right) = k_x \begin{Bmatrix} F_{zfl}\tanh\left(\varepsilon_x \kappa_{fl}\right)\cos\delta_f + F_{zfr}\tanh\left(\varepsilon_x \kappa_{fr}\right)\cos\delta_f \\ + F_{zrl}\tanh\left(\varepsilon_x \kappa_{rl}\right) + F_{zrr}\tanh\left(\varepsilon_x \kappa_{rr}\right) \end{Bmatrix} \tag{12}$$

From the above equations, the tuning factor k_x can be reached as follows.

$$k_x = \frac{m\left(\dot{v}_x - \dot{\psi}\cdot v_y\right)}{\begin{Bmatrix} F_{zfl}\tanh\left(\varepsilon_x \kappa_{fl}\right)\cos\delta_f + F_{zfr}\tanh\left(\varepsilon_x \kappa_{fr}\right)\cos\delta_f \\ + F_{zrl}\tanh\left(\varepsilon_x \kappa_{rl}\right) + F_{zrr}\tanh\left(\varepsilon_x \kappa_{rr}\right) \end{Bmatrix}} \tag{13}$$

The longitudinal forces can be obtained more accurate by Eq. (4) and (13), and then the robustness of the fault diagnosis is improved.

$$F_{xi} = k_x F_{zi}\tanh\left(\varepsilon_x \kappa_i\right), i = fl, fr, rl, rr \tag{14}$$

3. 3. Analysis Of The Correlation Between Each Sensor And Residual

This study is analysed the correlation between each sensor and Residual in order to verify the possibility of the fault isolation.

From Eq. (6), (13) and (14), these equations can be simplified to obtain the redundancy relation.

$$c_1 : F_{xi} = c_1\left(\delta_f, \dot{\psi}, v_x, v_y, F_z, \omega_w\right), i = fl, fr, rl, rr \tag{15}$$

In Eq. (15), v_y is calculated by Eq. (2) and (5), and F_z is calculated by Eq. (8). Similarly these equations can be simplified to obtain the redundancy relations.

$$c_2 : v_y = c_2\left(\delta_f, \dot{\psi}, v_x, F_x, F_z\right) \tag{16}$$

$$c_3 : F_y = c_3\left(\delta_f, \dot{\psi}, v_x, v_y, F_z\right) \tag{17}$$

$$c_4 : F_z = c_4\left(a_x, a_y\right) \tag{18}$$

Finally, by using the above information, the residuals are described by the following equation.

$$r_i : 0 = r_i(T_{mi}, F_{xi}, \omega_w) = r_i(T_{mi}, a_x, a_y, \delta_f, \dot{\psi}, v_x, \omega_w), i = fl, fr, rl, rr \quad (19)$$

From the above residuals, the fault table can be expressed as follows.

Table. 1. Fault table of residual

	a_x	a_y	δ_f	$\dot{\psi}$	v_x	ω_w	T_{mfl}	T_{mfr}	T_{mrl}	T_{mrr}
r_1	X	X	X	X	X	X	X			
r_2	X	X	X	X	X	X		X		
r_3	X	X	X	X	X	X			X	
r_4	X	X	X	X	X	X				X

Table. 1. shows that it is possible to fault isolation of the drive motors of the wheels when the other sensor information is assumed to be normal.

3. 4. Adaptive Threshold

Once the residual is generated and evaluated, it should be then compared with the limit value which is called the threshold. If the residual deviates from the threshold, a fault is declared as detected.

$$|r| > Th \quad (20)$$

where r is the residual value, and Th is the threshold value.

In this paper, the fault diagnosis algorithm uses vehicle models which do not fully agree with real processes due to model uncertainties. The generated residual then deviates from zero even without fault. If the threshold is not well set, it may generate false alarms through normal fluctuations of the variable. It is obvious that setting Th too high will reduce the sensitivity to the faults and setting Th too low will increase the false alarm rate.

Usually, Th is set empirically considering the maximum influence of the model uncertainties. In transient state, especially, these model uncertainties are more frequently occurred. Therefore, adaptive threshold is introduced to avoid these problems. The deviation of the residual depends on the amplitude and frequencies of the input excitation. The adaptive threshold method uses its variation. It is used that a high pass filter (HPF) for enlarging the threshold, on which the deviation and the amplitude of the input have an effect, and a low pass filter (LPF) for smoothing the threshold as Fig. 3. The time constants T_1 and T_2 are selected according to the dominating time constant of the system process. T_1/T_2 depends on the model uncertainty of the dynamics as shown by R. Isermann et al. (2008).

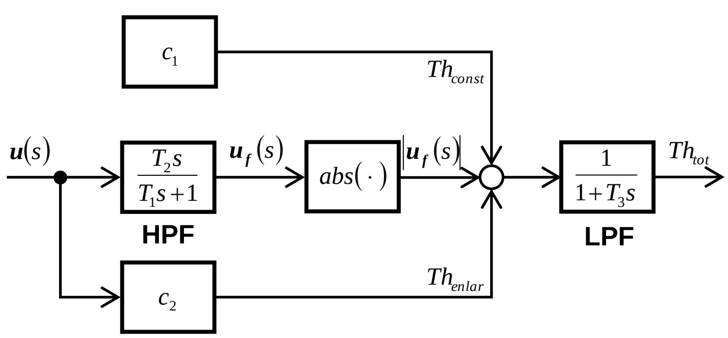

Fig. 3. Structure of the adaptive threshold generator

4. Simulation Results

The simulation was done to verify the proposed fault diagnosis algorithm. The simulation environment consists of the fault diagnosis algorithm and the vehicle dynamics simulation tool. The fault diagnosis algorithm were programmed by Matlab/Simulink®. A vehicle dynamics simulation package, CarSim®, was used to simulate vehicle dynamics.

The simulation condition is the straight driving with constant throttle (0.2, 0.5) at an initial vehicle speed 20km/h. The fault signal are applied from 5 to 7 seconds, and this fault signal was implemented the right rear (RR) drive motor torque 30% reduction.

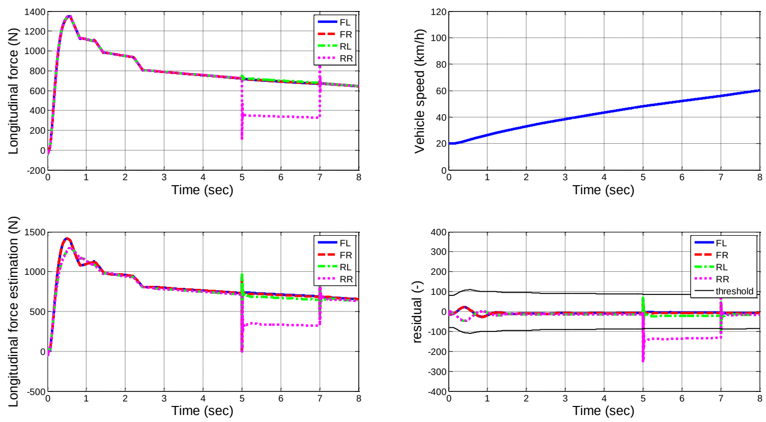

Fig. 4. Simulation result (Initial speed 20km/h, throttle=0.2 acceleration)

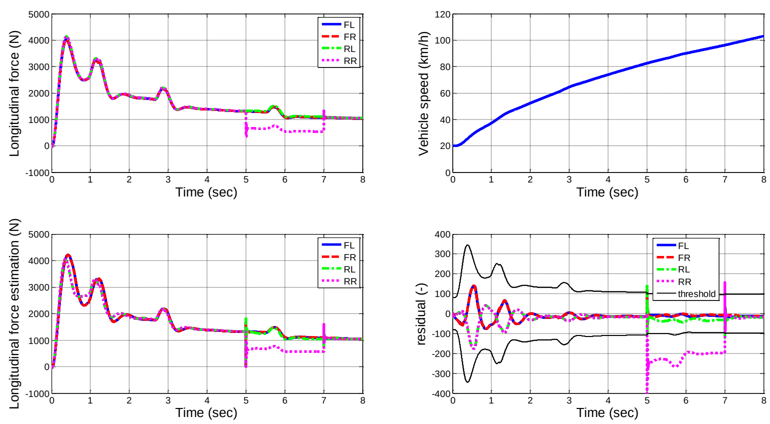

Fig. 5. Simulation result (Initial speed 20km/h, throttle=0.5 acceleration)

Fig. 3 and Fig. 4 show that the longitudinal force of each wheel are estimated very well. In addition the input signals of the vehicle (longitudinal slip) influence on the threshold adaptively at the start point. The results of the residuals are also shown; zero value represents fault free situation, and other values over the threshold represent faulty situation. In these results, the drive motor fault each wheel are detected and isolated.

5. Conclusion

This paper presents a fault diagnosis algorithm of the high-level for driving motor of In-wheel independent drive electric vehicle using vehicle dynamic analysis. In the future, this research can be expand into the integrated fault diagnosis research to improve the stability and reliability of the control by integrating with the low-level fault detection.

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References

Hori, Y. (1998). Traction Control of Electric Vehicle: Basic Experimental Results Using the Test EV “UOT Electric March”. *IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS*, 34(5), 1131-1138.

Hori, Y. (2004). Traction Control of Electric Vehicle: Basic Experimental Results Using the Test EV “UOT Electric March”. *IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS*, 51(5), 954-962.

Benbouzid, M.E.H. (2007). Advanced Fault-Tolerant Control of Induction-Motor Drives for EV/HEV Traction Applications: From Conventional to Modern and Intelligent Control Techniques. *IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY*, 56(2), 519-528.

Diallo, Demba. (2004). A Fault-Tolerant Control Architecture for Induction Motor Drives in Automotive Applications. *IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY*, 53(6), 1847-1855.

Parsa, Leila. (2007). Fault-Tolerant Interior-Permanent-Magnet Machines for Hybrid Electric Vehicle Applications. *IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY*, 56(4), 1546-1552.

El-Antably, Ahmed. (1993). System simulation of fault conditions in the components of the electric drive system of an electric vehicle or an industrial drive. *Industrial Electronics, Control, and Instrumentation (IECON)*, 2, 1146 – 1150.

Welchko, B.A. (2002). IPM Synchronous Machine Drive Response to a Single-Phase Open Circuit Fault. *IEEE TRANSACTIONS ON POWER ELECTRONICS*, 17(5), 764-771.

Jeong, Y.S. (2005). Fault Detection and Fault-Tolerant Control of Interior Permanent-Magnet Motor Drive System for Electric Vehicle. *IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS*, 41(1), 46-51.

Akin, B. (2009). DSP-Based Sensorless Electric Motor Fault-Diagnosis Tools for Electric and Hybrid Electric Vehicle Powertrain Applications. *IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY*, 58(6), 2679-2688.

Chow. E.Y. (1984). Analytical Redundancy and the Design of Robust Failure Detection Systems. *IEEE TMNSACTTONS OK AUTOMATIC CONTROL*, AC-29(7), 603-614.

Fang, X. (1994). A Double-Threshold-Testing Robust Method for Fault Detection and Isolation in Dynamic Systems. *American Control Conference*, 2, 1979-1983.

Song, B. (2005). Fault Tolerant Nonlinear Control with Applications to an Automated Transit Bus. *Vehicle System Dynamics*, 43(5), 331–350.

Kim, S. (2008). Fault Detection and Diagnosis of CAN-Based Distributed Systems for Longitudinal Control of All-Terrain Vehicle (ATV). *Journal of Institute of Control, Robotics and Systems*, 14(10), 983-990.

Mokhiamar, O. (2006). How the Four Wheels Should Share Forces in an Optimum Cooperative Chassis Control. *Control Engineering Practice*, 14(3), 295–304.

Isermann, R. (2006). Fault-Diagnosis Systems – An Introduction from Fault Detection to Fault Tolerance. 107-108, Springer.