Fault Detection via Stability Analysis for the Hybrid Control Unit of HEVs

Kyogun Chang and Yoon Bok Lee

Abstract—Fault detection determines fault existence and detecting time. This paper discusses two layered fault detection methods to enhance the reliability and safety. Two layered fault detection methods consist of fault detection methods of component level controllers and system level controllers. Component level controllers detect faults by using limit checking, model-based detection, and data-driven detection and system level controllers execute detection by stability analysis which can detect unknown changes. System level controllers compare detection results via stability with fault signals from lower level controllers. This paper addresses fault detection methods via stability and suggests fault detection criteria in nonlinear systems. The fault detection method applied to the hybrid control unit of a military hybrid electric vehicle can detect faults of the traction motor.

Keywords—Two Layered Fault Detection, Stability Analysis, Fault-Tolerant Control

I. INTRODUCTION

A fault is an unpermitted deviation with abrupt, incipient or intermittent patterns. The fault can cause a failure which is a permanent interruption and leads unstable states of the system. It is highly related to reliability, availability, maintainability, and safety and has been analyzed based on experimental data or operation variables to improve reliability, availability, maintainability, and safety. FMEA (Failure Mode and Effects Analysis) and FTA (Fault Tree Analysis) are useful procedures to analyze each potential failure mode in a product to determine the effects, its criticality, and cause [1]. Large amounts of experimental data about failure modes have been mainly provided for military applications.

However, new patterns of faults have been generated, as electric/electronic/software systems have been steeply becoming popular and their controllability has been delicately improved. As a result, interest in fault detection and diagnosis (FDD) has been growing in monitoring the ongoing faults and in system degradation. Precise fault detection becomes more and more critical to ensure system stability.

Yang, Jiang, and Cocquempont (2010) addresses the combination of general fault detection and energy-based fault detection. The novel energy-based on fault detection technique is concerned with the energy analysis related to dissipativity. They suggest stable switching strategies in hybrid systems.

Isermann(2006) discusses comparison of each fault detection methods and combination of different fault-detection methods. Depending on applications, different fault detection methods can be selected for better detection performance. Proper combination of different fault-detection makes use of their advantages and generates relevant analytical symptoms for integrated FDD.

Kim, Song and Song (2009) presents two layered FDD using decentralized and centralized schemes. Two layered fault detection improves detection capability of faults. They applied the two layered FDD scheme to an ATV to prove advantages of robustness and accuracy of fault detection.

This paper presents fault detection methods via stability analysis for the HCU (Hybrid Electric Vehicle) of a HEV. In Section 2, fault models and two layered fault detection are presented. Fault detection methods via stability of the HCU are discussed in Section 3. Section 4 proposes an example of application. A conclusion is made in Section 5.

II. FAULT MODELS AND TWO LAYERED FAULT DETECTION IN NONLINEAR SYSTEMS

A. Fault Models in Nonlinear Systems

Consider the general nonlinear system

\[ \dot{x} = f(x) + g(x)u \]

\[ y = h(x) \]

where \( x \in \mathbb{R}^n \) is the state, \( u \in \mathbb{R}^m \) is the input, and \( y \in \mathbb{R}^p \) is the output [2].

A fault is a deviation of at least one characteristic property under abnormal conditions that can make a system fail. A fault can cause an error which can result in failure ultimately [3]. The time dependent faults can be divided into abrupt, incipient, and intermittent faults (see fig. 1).

Fault models can be classified as additive faults and multiplicative faults. Basic equations can be expressed by
Additive fault model: \( Y(t) = Y_0(t) + f(t) \)

Multiplicative fault model: \( \tilde{Y}(t) = A \tilde{U}(A) + fU(t) \).

Fig. 2 System Models with Additive and Multiplicative Faults

Additive faults such as input faults \( f_u \) and output faults \( f_y \) in fig. 2 in the closed loop system model will be modeled by

\[
\begin{align*}
\dot{x} &= f(x) + g(x)u + \Delta f(x)
\end{align*}
\]

\[
\begin{align*}
y &= h(x) + \Delta h(x).
\end{align*}
\]

Therefore, the nonlinear systems with faults can be physically modeled as equation (2) and equation (3).

### B. Two Layered Fault Detection Methods

Fault detection determines fault existence and time of detection and its methods can be classified by limit checking, trend checking, model based detection, and data-driven detection [3]. Each fault detection method has advantages and disadvantages. Parity equations are simple to design and to implement but they are problematic about robustness with regard to parameter changes. Parity equations cannot design faulty systems with multiplicative faults, too. State estimation can react very fast to sudden faults but state estimation is limited for nonlinear processes. On the other hand, parameter estimation is suitable for multiplicative faults [3].

Two layered fault detection allows for more precise detection because it provides cross checks with different fault detection methods [4]. Component level controllers use decentralized fault detection while system level controllers apply centralized fault detection. The hybrid control unit of the hybrid electric vehicle will be a system level controller. If both detection methods are different, fault detection by cross checks can be precisely performed.

Component level controllers use general limit checking and trend checking. The thresholds for limit checking are mostly chosen by signal or process models and experimental data. Trend checking of the monitored variable is useful because it can be obtained earlier than detection time by limit checking of absolute value [3].

Normal fluctuations of measured signals are prohibited from generating fault alarm and fault deviation has to be detected quickly. The debouncing filter isolates transient fluctuations by limit checking over a prescribed period of debounce time. Fig. 3 shows an example of debouncing filters for minimizing faulty detection by fluctuations.

Fault detection methods via stability analysis of nonlinear systems can be adapted for system level controllers such as the HCU in the hybrid electric vehicle (HEV). Fault detection via stability can also produce control input and control stability effectiveness.

### III. FAULT DETECTION METHODS BASED ON STABILITY FOR THE HCU

Fault detection methods of system level controllers are usually different from fault detection methods of component level controllers. This section discusses fault detection methods via nonlinear stability analysis for the HCU which is capable of detecting unknown parameter changes.

#### A. Fault Detection via Passivity or Dissipativity

Consider the affine nonlinear system

\[
\begin{align*}
\dot{x} &= G(x(t), u(t), f(x)) + g(x)u + \Delta(x) \quad (4)
\end{align*}
\]

\[
\begin{align*}
y &= h(x).
\end{align*}
\]

A nonlinear system with \( \Delta \equiv 0 \) is passive if there exists a nonnegative Lyapunov function \( V : X \to \mathbb{R} \), with \( V(0) = 0 \), called the storage function. An inner product \( \langle u(t), y(t) \rangle \), such that for all initial states, are the supply rate [2]. Passivity and strict passivity can be described by

\[
\begin{align*}
\langle u(t), y(t) \rangle &\geq \beta(\text{passivity}) \\
\langle u(t), y(t) \rangle &\geq \delta \| u \|^2_{L_2} \text{ or } L_\infty + \beta(\text{strict passivity})
\end{align*}
\]

The dissipativity inequality is given as

\[
\begin{align*}
V(x(t)) - V(x(0)) \leq \int_0^t W(y^T(x(s))u(s))ds 
\end{align*}
\]

where \( x(t) \) is the states at time \( t \) and \( w(t) = w(u(t), y(t)) \) is supply rate. If the inequality is violated, the control law is inadequate and the fault is generated. The energy dissipativity property can induce a fault detection law which is expressed by

\[
\begin{align*}
Cr_{\text{DSS}} &= V(x(t)) - V(x(0)) - \int_0^t W(y^T(s))u(s)ds
\end{align*}
\]

If \( Cr_{\text{DSS}} > 0 \), a fault can be conjectured due to \( Cr_{\text{DSS}} \leq 0 \). Yang, Jiang, and Cocquempont (2010) presented several examples and adapted switching rules.
B. Fault Detection via Input-Output Stability

A system is called to have a finite gain, if there exists a constant $\gamma(H) < \infty$, which is the gain of $H$ and a constant $\beta \in \mathbb{R}^*$ such that

$$\|y(t)\|_{L_{loc}^\infty} \leq \gamma(H)\|u(t)\|_{L_{loc}^\infty} + \beta \quad \left(\forall t \in [0, \infty)\right)$$

Systems with finite gain are said to be finite-gain-stable [5]. A fault detection rule via input-output stability property can be defined by

$$C_{foss} = \left\|y(t)\right\|_{L_{loc}^\infty} - \left\|y(H)u(t)\right\|_{L_{loc}^\infty} + \beta$$

This criterion helps high level controllers detect faults by comparison between input and output.

C. Fault Detection via Output-to-Input Stability

Systems with $f_x = 0$ are called output-input-stable, if there exists a positive integer $N$, a function $\beta$ of class $KL$ (decrescent function), and a function $\gamma$ of class $K_{\infty}$, such that for every initial state $x(0)$ and every input $u \in \ell_{N-1}$ (N-l order differentiable) its solution $x(t)$ satisfies

$$\left\|x(t)\right\|_{L_{loc}^\infty} \leq \beta(x(0), t) + \gamma\left(\|u\|_{L_1}\right)$$

for $\forall t \in [0, t]$. The fault detection rule can be derived by

$$C_{fios} = \left\|y(t)\right\|_{L_{loc}^\infty} - \left\|y(H)u(t)\right\|_{L_{loc}^\infty} + \beta$$

If $C_{fios} < 0$, given system is unstable and any fault has been generated.

D. Fault Detection via Input-to-State Stability

The system with $f_x = 0$ is called input-to-state-stable [2][5], if there exist a function $\beta$ of class $KL$, and a function $\gamma$ of class $K_{\infty}$, such that for every initial state $x(0) \in D$ and every input $u \in D$, its solution $x(t)$ satisfies

$$\left\|x(t)\right\|_{L_{loc}^\infty} \leq \beta(x(0), t) + \gamma\left(\|u\|_{L_1}\right)$$

for $\forall t \leq t$. The fault detection rule can be defined by

$$C_{fiss} = \left\|x(t)\right\|_{L_{loc}^\infty} - \left\|x(H)u(t)\right\|_{L_{loc}^\infty} + \beta$$

The detection rule is useful to recognize fault existence between inputs and states.

IV. APPLICATION

A. Model of Interior Permanent Magnet Synchronous Motor

The IPMSM (Interior Permanent Magnet Synchronous Motor) has three-phase windings excited with a balanced three-phase current and can produce field torque and reluctance torque simultaneously. Since two types of torques are produced, the efficiency of IPMSM is relatively higher. That is the reason that the IPMSM is often applied as traction motors of the hybrid electric vehicle (HEV) and the electric vehicle. The model of IPMSM is as following [7][8]:

$$\dot{i}_q = \frac{1}{L_q} \left[ -r_i i_q + E_q - \omega_i (L_d i_d + \lambda_m) \right]$$

$$\dot{i}_d = \frac{1}{L_d} \left[ -r_i i_d + E_d + \omega_i L_q i_q \right]$$

$$\dot{\omega}_d = \frac{3}{2 J} \left[ \lambda_m i_d + (L_d - L_q) i_d i_q \right] - \frac{T_L}{J}$$

where $L$, $i$, and $E$ are inductances, currents, and voltages angle $\alpha$ and $\delta$ axes, respectively. $r$ in equation (12) is resistance of the stator windings, $\omega_i$ is angular velocity of the rotor, $J$ is inertia moment of the rotor, $P$ is the number of poles, and $T_L$ is the load torque from external load and friction.

The torque of the IPMSM is given as

$$T_m = \frac{3}{2 J} \left[ \lambda_m i_d + (L_d - L_q) i_d i_q \right]$$

Without considering parameter changes, the observer equations for adaptive control are expressed by

$$\dot{i}_q = \frac{1}{L_q} \left[ -r_i i_q + E_q - \omega_i (L_d i_d + \lambda_m) \right]$$

$$\dot{i}_d = \frac{1}{L_d} \left[ -r_i i_d + E_d + \omega_i L_q i_q \right]$$

$$\dot{\omega}_d = \frac{3}{2 J} \left[ \lambda_m i_d + (L_d - L_q) i_d i_q \right] - \frac{T_L}{J} + u$$

$$\tilde{y} = \tilde{\omega}_d$$

$u$ is the control input and $\tilde{y}$ is an estimated variable. Substituting equation (12) from equation (13) yields

$$\dot{i}_q = \frac{1}{L_q} \left[ -r_i i_q - \omega_i L_d i_d \right]$$

The Lyapunov function candidate is chosen by

$$V = \frac{1}{2} \dot{i}_q^2 + \frac{1}{2} \dot{i}_d^2 + \frac{1}{2} \dot{\omega}_d^2$$

$$\dot{V} = -\frac{r_i}{L_q} i_q^2 - \frac{r_i}{L_d} i_d^2 - \frac{3P}{4J} [\lambda_m i_d + (L_d - L_q) i_d i_q] + u [\tilde{\omega}_d]$$

A control law can be defined by

$$u = -\frac{3P}{4J} [\lambda_m i_d + (L_d - L_q) i_d i_q] + \left( \frac{L_d}{L_q} - L_q \right) \tilde{i}_q$$

Then, $\dot{V} = -\frac{r_i}{L_q} i_q^2 - \frac{r_i}{L_d} i_d^2 \leq 0$. Since $V \geq 0$ and $\dot{V} \leq 0$,
\[ \lim_{t \to \infty} V(t) \] exists and it is finite. Errors are \( L_{q_0} \) and \( L_2 \). Therefore, all errors \( (\tilde{i}_q, \tilde{i}_d, \text{and} \tilde{\omega}_r) \) converge to zero while \( t \to \infty \) by Barbalat’s Lemma.[6]

**B. Simulation**

The IPMSM is highly applicable for traction motors of the hybrid electric vehicles. The military hybrid electric vehicle has been developing for commercial and military applications and fig. 4 shows its prototype. An IPMSM equipped in the military hybrid electric vehicle with nominal parameters in Table 1 is simulated. The results of simulation are shown from figs 5 to 7. Initial errors of q axis and d axis currents are 35(A) and -5(A). Initial error of rotor speed is 20 (rad/s).

![Fig. 4 A Military Hybrid Electric Vehicle and its IPMSM](image)

**Table 1**

<table>
<thead>
<tr>
<th>IPMSM Parameters</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rated output power (kW)</td>
<td>65</td>
</tr>
<tr>
<td>Magnetic flux linkage (Wb)</td>
<td>0.533</td>
</tr>
<tr>
<td>Number of poles</td>
<td>8</td>
</tr>
<tr>
<td>Stator resistance (ohm)</td>
<td>2.875</td>
</tr>
<tr>
<td>q-axis inductance (mH)</td>
<td>456</td>
</tr>
<tr>
<td>d-axis inductance (mH)</td>
<td>216</td>
</tr>
<tr>
<td>Inertia (kg-m(^2))</td>
<td>0.069</td>
</tr>
</tbody>
</table>

![Fig. 5 Simulated Dynamic Errors of Operation Variables](image)

In fig. 6, Lyapunov function exists in positive range but the derivative of Lyapunov function locates at negative range. Therefore, the system is stable without any fault.

![Fig. 6 Lyapunov Function and its Derivative](image)

![Fig. 7 Stored and Supplied Energy from Equation (5) and Dissipativity Criteria from Equation (6)](image)

Fig. 8 shows fault detection by unpermitted actual current change from 0(A) to 100(A) along q-axis at 5s. Since the dissipativity criterion crosses over zero at 5s, the fault is detected in fig. 8. Using dissipativity stability, fault detection can be achieved effectively.

**V. CONCLUSION**

This paper proposed two layered fault detection methods to enhance the reliability and safety of the system. Two layered fault detection by component level controllers and system level controllers were defined. Component level controllers detected
fault by limit checking, trend checking, and model-based detection. The debouncing filter for avoiding faulty alarm by transient fluctuation was discussed. System level controllers used fault detection methods via stability analysis which can detect unknown changes and compare with fault signals from lower level controllers. Fault detection methods and detection criteria via stability in nonlinear systems were developed and were applied to the HCU in order to detect faults of the traction motor, an IPMSM.

Fault detections via stability have limitation about fault isolation even though the fault detection method is helpful to check faults by unknown features. As future work, improving detection performance with changing different pairs between system level FDD and component level FDD has to be preceded. Integrated FDD will be designed and implemented in the hybrid control unit of the hybrid electric vehicle.

REFERENCES


Kyogun Chang was born on March 7th, 1969 in Jeonju, Korea. He received the M.Sc. degree in precision mechanical engineering from Chonbuk National University, Korea and PhD degree in mechanical engineering from The University of Texas at Austin, TX, USA, in 1995 and 2006, respectively. He is currently a senior researcher in Agency for Defense Department, Daejeon, Korea. His major interests are fault tolerant system design for military hybrid electric vehicles.

Yoon Bok Lee was born on February 10th, 1960 in Suwon, Korea. He received the B.Sc. degree in mechanical engineering from Ajou University in 1982 and the M.Sc. degree in mechanical engineering from KAIST in 1995. He also received PhD degree in mechanical engineering from Chungnam National University, Korea, in 2004. He is currently a principal researcher and a project manager of military hybrid electric vehicles in Agency for Defense Department, Daejeon, Korea. His major interests are active suspension control system and propulsion power/energy control for military hybrid electric vehicles.