Motion Sensor Fault Detection and Failsafe Logic for Vehicle Stability Control Systems (VSCs)

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The design of a reliable and failsafe control system requires that sensor failures be detected and identified within acceptable time limit so that system malfunction can be prevented. This paper presents a model-based approach to sensor fault detection with applications to vehicle stability control systems. The effectiveness of the proposed method is illustrated through test data-based evaluation. Vehicle test data-based evaluation results show that the proposed fault management scheme can be used for the design of a failsafe VSCs.

Key Words : Fault Detection, Vehicle Control System, Stability Control, Sensor

1. Introduction

Vehicle active safety systems and driver assistance systems have been popular research and development topics since the 1990's for enhancing vehicle safety and reducing driver work load. The vehicle stability control system (VSCs) is an active safety system for road vehicles which stabilizes the vehicle dynamic behavior in emergency situations such as spinning, drift out and roll over (Van Zanten, 2000 ; Tseng, 1999 ; Ungoren and Peng, 2004). The VSCs has been available for vehicles with an electro hydraulic brake system since the 1990's and is evolving for robust performance in combination with active front steering. As in any control system, fault detection and failsafe operation of the VSCs is necessary for a practical system solution. The design of reliable and failsafe VSCs requires that sensor failures be detected and identified within acceptable time limits so that system malfunction can be prevented. The principal tradeoff to be made in designing a redundant sensor system is that of hardware redundancy versus the complexity and robustness problems of the software for analytic redundancy (White and Speyer, 1987). A dynamic model based fault detection scheme has been presented in the literature (Tseng, 1999 ; White and Speyer, 1987 ; Fennel and Ding, 2000). It has long been recognized that an adaptive threshold is an effective way to solve the problem caused by model uncertainties. Fault detection based on adaptive fuzzy thresholds was proposed by Frank (Duisberg and Frank, 0000). In this paper, motion sensor fault detection and failsafe logic for VSCs is proposed.

A three degree-of-freedom (3 DOF) vehicle planar model and a bicycle vehicle model have been used for analytic redundancy of vehicle sensors in a VSCs, i.e., yaw rate sensor, steering angle sensor and lateral accelerometer. The main difficulty of the model based fault detection schemes lies in the model uncertainties. In order to improve the accuracy of the model-based predictions of the sensor outputs, effective tire radius

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and roll angle have been estimated and used in combination with the 3 DOF vehicle model. The proposed fault management scheme has been evaluated using both a validated vehicle simulator and vehicle test data. Vehicle test data-based evaluation results show that the proposed fault management scheme can be used for the design of a failsafe VSCs.

2. Vehicle Model

2.1 Full vehicle model

Simulation studies have been conducted using a full three-dimensional vehicle simulator validated by vehicle test data [14]. The vehicle model used in this study is a full three-dimensional vehicle representation with six degrees of freedom for the vehicle body, four states for each suspension, one state for each wheel speed, an engine-powertrain model, and a Pacjeka tire model. The three dimensional vehicle model is depicted in Figure 1.

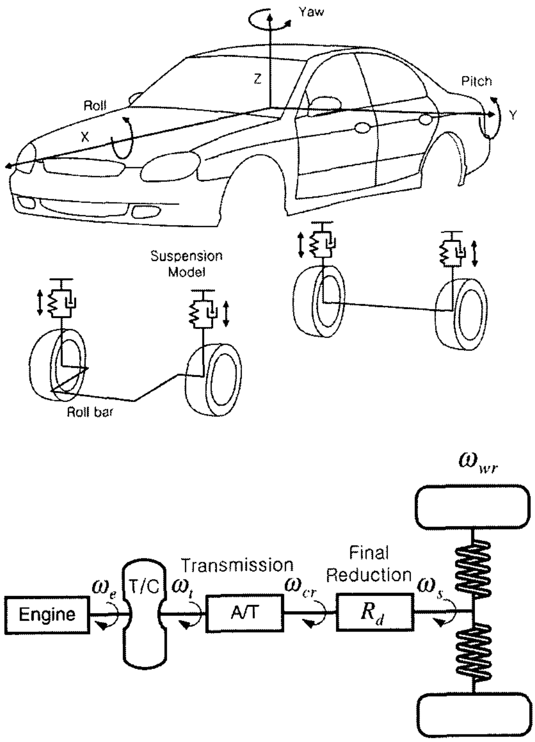


Fig. 1 Three-dimensional vehicle model

2.2 Vehicle sub-models for analytic redundancy

A VSCs controller uses the following sensors:

- a yaw rate sensor
- a lateral acceleration sensor
- a steering wheel angle sensor
- four wheel angular speed sensors

A fault detection scheme for the yaw rate sensor, the lateral acceleration sensor and the steering wheel angle sensor has been developed in this study under the assumption that the four wheel speed sensors are proven to be fault-free by other fault management modules such as the Antilock Brake Systems (ABS).

Four redundant sub-models can be used for the detection of faults in each sensor. The redundant sub-models have been obtained using kinematics relationships and a bicycle model of a vehicle. The mathematical models for the yaw rate sensor are as follows:

yaw rate sensor model 1, Y1, $\gamma_1 = \dfrac{v_{fr} - v_{fl}}{d}$

yaw rate sensor model 2, Y2, $\gamma_2 = \dfrac{v_{rr} - v_{rl}}{d}$

yaw rate sensor model 3, Y3, $\gamma_3 = \dfrac{a_y}{v_{ref}}$

yaw rate sensor model 3, Y4,

$$\gamma_4 = \frac{\delta}{r_s \cdot l} \frac{v_{ref}}{\left(1 + \left(\frac{v_{ref}}{v_{ch}}\right)^2\right)}$$

where $v_{(\cdot)}$ is wheel speed, the subscript fr, fl, rr, and rl represent front right, front left, rear right and rear left, respectively, d is track width, a_y is lateral acceleration, v_{ref} is vehicle longitudinal speed, δ is steering wheel angle, r_s is steering ratio, l is wheel base, and v_{ch} is the characteristic speed of the vehicle. The four wheel speeds are computed using effective tire radii and measured wheel angular speed as follows:

$$v_{(\cdot)} = r_{e(\cdot)} \cdot \omega_{(\cdot)}$$

where $r_{e(\cdot)}$ is the effective tire radius and $\omega_{(\cdot)}$ is the wheel angular speed. The effective tire radius is estimated using lateral acceleration as follows:

$$r_{e(\cdot)}=r_{n(\cdot)}-\frac{F_{z(\cdot)}}{K_{t(\cdot)}}$$

$$F_{zfl}=\frac{1}{2\cdot d}\left(\frac{M\cdot l_r}{l}\cdot g\cdot d-\frac{M\cdot l_r}{l}\cdot h\cdot a_{lat}-K_r\cdot k\cdot a_y\right)$$

$$F_{zfr}=\frac{1}{2\cdot d}\left(\frac{M\cdot l_r}{l}\cdot g\cdot d+\frac{M\cdot l_r}{l}\cdot h\cdot a_{lat}+K_r\cdot k\cdot a_y\right)$$

$$F_{zrl}=\frac{1}{2\cdot d}\left(\frac{M\cdot l_f}{l}\cdot g\cdot d-\frac{M\cdot l_f}{l}\cdot h\cdot a_y\right)$$

$$F_{zrr}=\frac{1}{2\cdot d}\left(\frac{M\cdot l_f}{l}\cdot g\cdot d+\frac{M\cdot l_f}{l}\cdot h\cdot a_y\right)$$

where $r_{n(\cdot)}$ is nominal tire radius, $K_{t(\cdot)}$ is tire stiffness, $F_{z(\cdot)}$ is vertical tire force, M is vehicle mass, l_r and l_f are distances from mass center to rear wheel and front wheel, respectively, g the gravitational constant, h roll center height, K_r roll bar stiffness, and k is a roll constant.

Four redundant sub-models for the lateral acceleration sensor can be written as follows:

lateral acceleration sensor model 1, A1,

$$a_1=v_{ref}\frac{v_{fr}-v_{fl}}{d}$$

lateral acceleration sensor model 2, A2,

$$a_2=v_{ref}\frac{v_{rr}-v_{rl}}{d}$$

lateral acceleration sensor model 3, A3,

$$a_3=v_{ref}\cdot\gamma$$

lateral acceleration sensor model 4, A4,

$$a_4=\frac{\delta}{r_s\cdot l}\frac{v_{ref}^2}{\left(1+\left(\frac{v_{ref}}{v_{ch}}\right)^2\right)}$$

where γ is the yaw rate.

Four redundant sub-models for the steering wheel angle sensor can be written as follows:

steering wheel angle sensor model 1, S1,

$$\delta_1=\frac{r_s\cdot l}{v_{ref}}\left(1+\left(\frac{v_{ref}}{v_{ch}}\right)^2\right)\left(\frac{v_{fr}-v_{fl}}{d}\right)$$

steering wheel angle sensor model 2, S1,

$$\delta_2=\frac{r_s\cdot l}{v_{ref}}\left(1+\left(\frac{v_{ref}}{v_{ch}}\right)^2\right)\left(\frac{v_{rr}-v_{rl}}{d}\right)$$

steering wheel angle sensor model 3, S3,

$$\delta_3=\frac{r_s\cdot l}{v_{ref}}\left(1+\left(\frac{v_{ref}}{v_{ch}}\right)^2\right)\cdot\gamma$$

steering wheel angle sensor model 4, S4,

$$\delta_4=\frac{r_s\cdot l}{v_{ref}^2}\left(1+\left(\frac{v_{ref}}{v_{ch}}\right)^2\right)$$

3. Model-Based Fault Detection and Failsafe Logic

3.1 Redundant signal generation

Figure 2 shows the structure of the model-based fault detection and failsafe logic for the VSCs. The logic consists of redundant signal generator, driving situation decision unit, residual evaluation unit, threshold adaptation unit, and sensor fail decision unit. Four redundant signals for each of the yaw rate, the lateral acceleration and the steering wheel angle are computed by the sub-models described in section 2 using the measured signals. The signals used for the redundant signal computation are the vehicle reference speed, v_{ref}, the lateral acceleration, a_y, the yaw rate, γ, the steering wheel angle, δ, and the four wheel speeds, v_{rf}, v_{fl}, v_{rr}, and v_{rl}.

3.2 Identification of driving situations

The driving situations are divided into three groups based on the errors between the actual signals and the redundant signals computed by the sub-models: Steady Driving (SD), Transient Driving (TD), and No Decision Driving (NDD) situations. The errors between the actual signal and the redundant ones are due to model error, parametric uncertainties and measurement noises.

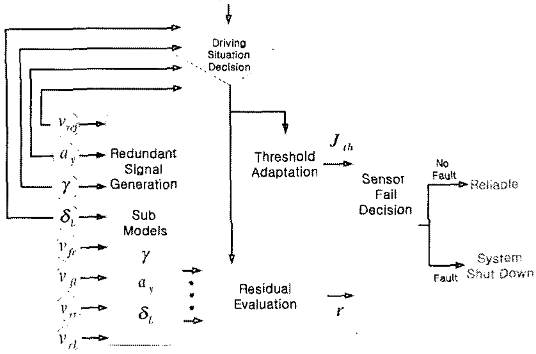


Fig. 2 Scheme of Model-based Fault Detection and Failsafe Logic

The driving situation decision algorithm has been designed considering validity conditions of the sub-models. The errors become large in cases when wheels are in slip, or when the steering wheel angle is large or when the magnitude of the longitudinal acceleration is large, etc. A driving situation decision unit has been designed based on an investigation into vehicle driving test data and vehicle simulation results for alternative driving situations. The vehicle simulations have been conducted using the validated full three-dimensional vehicle simulator and a simplified bicycle model. Identification of the deriving situations has been conducted using the lateral acceleration, a_y, the vehicle reference velocity, v_{ref}, the yaw rate, γ, the steering wheel angle, δ, and the longitudinal acceleration, a_x, as follows:

The driving situation is the SD if
$|\Delta a_{y,f}| < a_{y,c1}$, $|a_x| < a_{x,c}$ and $|\delta| < \delta_c(v_{ref})$

The driving situation is the TD if
$a_{y,c1} \leq |\Delta a_{y,f}| \leq a_{y,c2}$, $|a_x| < a_{x,c}$ and $|\delta| < \delta_c(v_{ref})$

The driving situation is the NDD if
$|\Delta a_{y,f}| > a_{y,c2}$, or $|a_x| \geq a_{x,c}$, or $|\delta| \geq \delta_c(v_{ref})$

$$\Delta a_{y,f} = \frac{1}{\tau_a s + 1}(a_y - v_{ref} \cdot \gamma) \tag{1}$$

where $a_{y,c1}$ and $a_{y,c2}$ are critical lateral accelerations, $a_{x,c}$, δ_c, and τ_a are critical longitudinal acceleration, critical steering wheel angle, low pass time constant, respectively, which have been determined and tuned based on the vehicle test data analysis and simulation studies. It should be noted that the critical steering wheel angle, $\delta_c(v_{ref})$, is represented as a function of the vehicle reference speed.

3.3 Threshold adaptation and residual generation

Since the model uncertainties depend strongly on the driving situations, it is necessary to use adaptive thresholds and different residual generation strategies depending on the driving situation of the vehicle. Alternative residual evaluation methods such as simple threshold logic, statistical decision, pattern recognition, fuzzy decision logic, and neural networks can be used for fault detection (Duisberg and Frank, 0000). It has long been recognized that an adaptive threshold is an effective way to solve the problem caused by the model uncertainties. An adaptive threshold has been developed as follows:

$$J_{th} = \begin{cases} \textit{small} & \text{if SD} \\ \textit{large} & \text{if TD} \\ \textit{very large} & \text{if NDD} \end{cases}$$

Since the magnitudes of the errors between the sensor sub-models and actual sensor output largely depend on model uncertainties, parametric errors and measurement noises and the model uncertainties are largely influenced by the driving situation where the vehicle is, the magnitude of the thresholds should be determined considering the driving situations of our interests. The thresholds have been determined based on the investigation of test vehicle measurements and simulation data under alternative driving situations. Sensor characteristics have been analyzed using the test vehicle measurements. The errors due to the model uncertainties have been investigated using the validated full three-dimensional vehicle simulator and the bicycle vehicle model.

"Majority principle" and "minimum of all" schemes (Fennel and Ding, 2000) have been used for the generation of residuals. In case of the "SD" driving situation, the residual, r, has been computed as follows:

$$r = y - \hat{y}_{i2}$$

where y is a measured sensor output and $\hat{y}_{i2}$ is a sensor model output selected such that

$$\hat{y}_{i1} \leq \hat{y}_{i2} \leq \hat{y}_{i3}$$

and

$$|\bar{y} - \hat{y}_{i1}|,\ |\bar{y} - \hat{y}_{i2}|,\ |\bar{y} - \hat{y}_{i3}| < |\bar{y} - \hat{y}_j|$$

$$j \neq i1,\ i2,\ i3 \quad j \in \{1, \cdots, n, n+1\}$$

$$\bar{y} = \frac{1}{n+1}\left(\sum_{i=1}^{n} \hat{y}_i + y\right)$$

n : the number of sub-models
$\hat{y}_i$: output of the sensor sub-model i.

When the vehicle is in "TD" or "NDD," the residual has been computed as

$$r=\min_j\{|r_j|=|y-\hat{y}_j|,\ j=1,\ \cdots,\ n\}$$

This implies that the residual is the smallest one among all the available residual signals.

3.4 Sensor fail decision

A non-dimensional continuous fault index is used to evaluate sensor fails. This fault index (FI) is computed using the residual and the adaptive threshold :

$$FI=FI(r,\ J_{th})=1-c^{-\frac{r}{J_{th}}}$$

where c is a constant. The FI is in between 0 and 1. A small value of the FI implies that the sensor is highly reliable and a large FI implies that the possibility of the sensor fail is very high. In this study, the sensor fail decision has been made as follows :

If $FI>\alpha$, then the sensor failed and system shut down.

IF $FI\leq\alpha$, then the sensor is reliable.

where α is a critical index value and an α of 0.9 has been used in this study.

4. Test Results : Vehicle Test Data-Based Evaluation

Vehicle test data have been used to illustrate the effectiveness of the proposed fault detection and failsafe logic. The test vehicle measurements have been obtained for typical driving situations such as constant steer input, lane change, slalom, and step steer maneuvers.

4.1 Constant steer input maneuver

Figure 3 shows the test results for a constant steering input maneuver with no sensor fault. Vehicle speed was kept at a constant 71 km/h and steering wheel angle was 43 degrees. Comparisons between the actual and redundant signals for the yaw rate, lateral acceleration and the steering wheel angle and fail indexes are shown in Figure 3. It is interesting to note that sub-models 1, 3 and 4 are very close to the actual sensors in this driving situation while sub-model 2 shows significant discrepancies. It is shown that all the fail indexes are far below 0.9 and all the sensors are highly reliable.

Figure 4 shows the test results for a constant steering input maneuver with the yaw rate sensor fault. It has been assumed in this case that the yaw rate sensor fails at 4 seconds and its output signal is reduced to 50% of the actual one. A comparison between actual yaw rate sensor output signal, fault signal, and sub-model outputs are compared in the first part of Figure 4(a). The residual and threshold are compared in the second part of

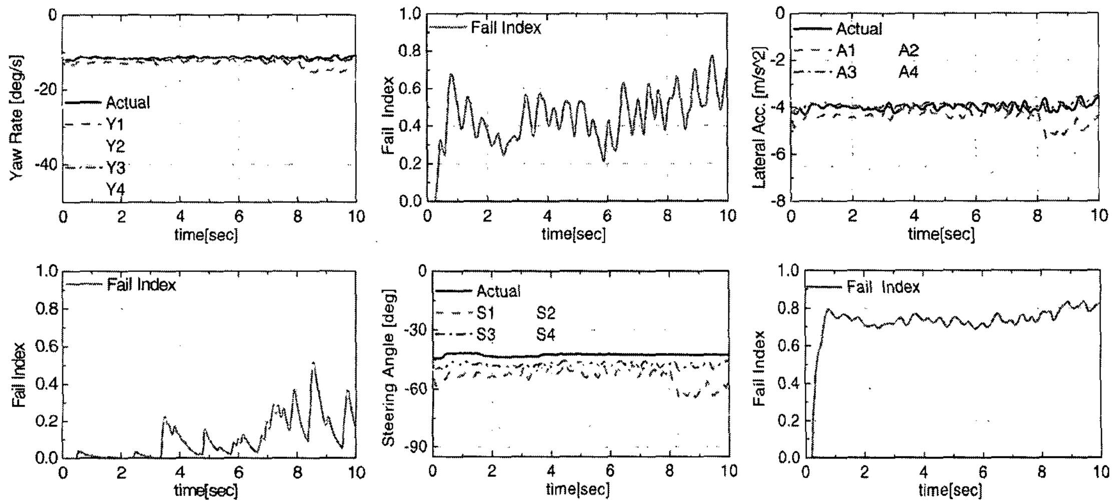
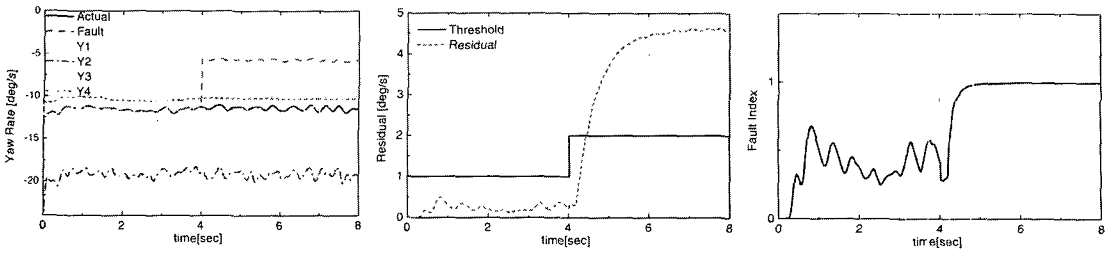
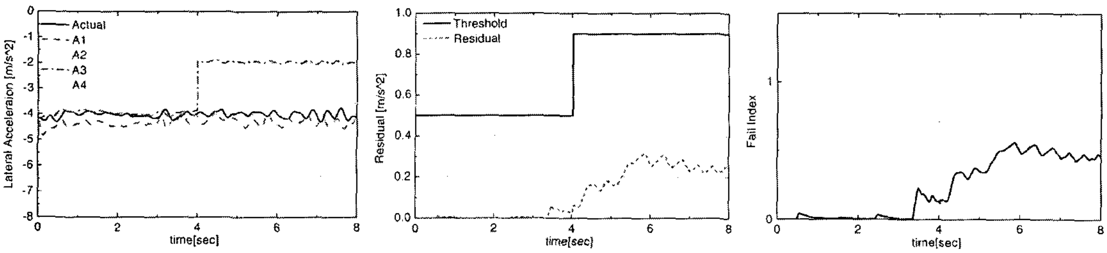


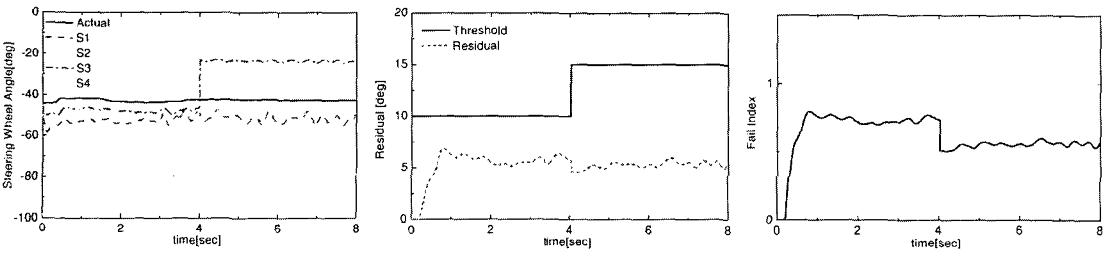
Fig. 3 Experimental test results (Constant steer input maneuver, no fault)



(a) Yaw rate sensor



(b) Lateral accelerometer



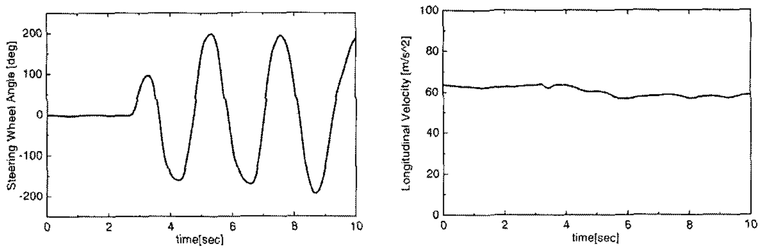
(c) Steering wheel residual

Fig. 4 Experimental test results (Constant steer input maneuver, Yaw rate sensor fault)

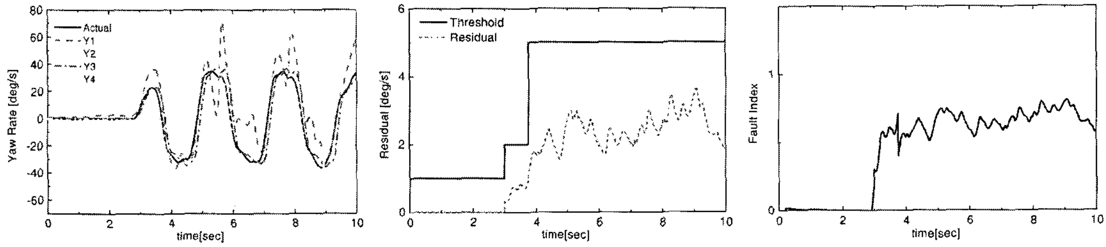
Figure 4(a). The fault indexes are also shown in the third part. Similar comparisons and the fail indexes for the lateral accelerometer and the steering wheel angle are shown in Figure 4(b) and(c), respectively. It is illustrated in Figure 4(a) that the yaw rate sensor fault is detected at 4.3 seconds. The fail index converges to 1 after 4.3 seconds and this implies that the sensor is failing. It is illustrated in Figure 4(b) and (c) that the residuals are far below the thresholds and the fail indexes are far below the critical value in the cases of the lateral accelerometer and the steering wheel angle sensor. It is illustrated that a yaw rate sensor fault can be effectively detected with the proposed fault detection logic.

4.2 Slalom — no decision driving (NDD) situations

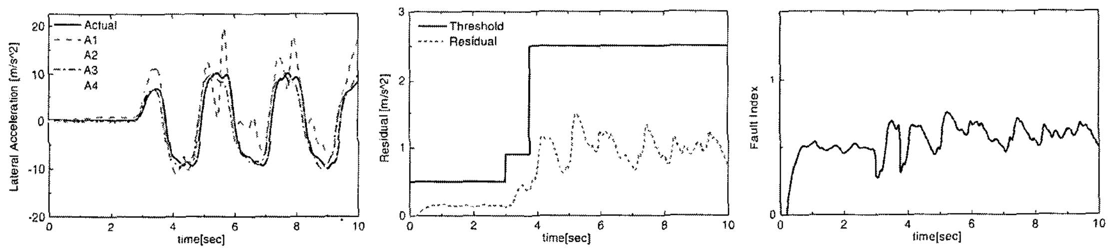
Test results for a slalom maneuver are shown in Figure 5. The steering wheel angle and vehicle velocity are depicted in Figure 5(a). The vehicle longitudinal velocity was maintained in a range of 58 to 62 km/h. Comparisons between sensor and sub-model outputs, the residual and thresholds and the fail indexes for the yaw rate, the lateral accelerometer and the steering wheel angle sensors are shown in Figure 5(b), (c) and (d), respectively. In this case, the modeling errors become significant and the sub-model output errors become large. In this slalom maneuver, the driving situation becomes TD and NDD, and the thresholds are set high and very high at the beginning and at 3.8 seconds, respectively. The thresholds are set to be very high in the NDD driving situation after 3.8 seconds and all the fail indexes are kept at small values. These test results indicate that the proposed driving situation decision logic works effectively.



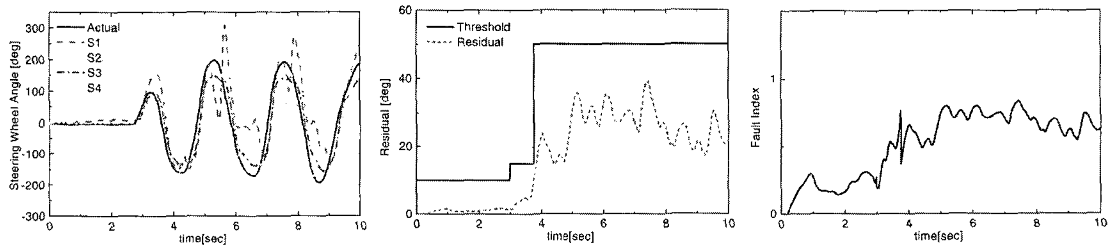
(a) Steering wheel angle and vehicle velocity



(b) Yaw rate sensor



(c) Lateral accelerometer



(d) Steering wheel residual

Fig. 5 Experimental test results (Slalom Test-No Decision Driving Situation)

5. Conclusions

A model-based fault management scheme for applications to vehicle stability control systems has been presented in this paper. A three degree-of-freedom vehicle planar model and a bicycle model have been used for analytic redundancy of yaw rate sensor, lateral accelerometer, and steering angle sensor. Thresholds have been adapted depending on the vehicle driving situations. A driving situation identification scheme has been designed. The vehicle control system malfunction due to sensor failure can be prevented by the use of analytic redundancy. The effectiveness of the proposed method is illustrated through test data-based evaluation. Vehicle test data-based evaluation results show that the proposed fault management scheme can be used for the design of a failsafe VSCs.

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