FAULT DETECTION OF A STEERING WHEEL SENSOR SIGNAL IN AN ACTIVE FRONT STEERING SYSTEM

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Abstract: Active front steering is an emerging steering technology for passenger cars that realizes a mechatronic superposition of an angle to the hand steering wheel angle that is prescribed by the driver. This contribution describes algorithms, used to ensure – along with others – the overall safety of the system (i.e. preventing hazardous behavior). A kinematic constraint, modelled as a dynamic system, is used to estimate the steering wheel angle. This estimated signal is compared with the measured signal. Using change detection algorithms typical failure patterns of the steering wheel sensor are detected quite easily. Sample results and measurements from a prototype vehicle are presented.*Copyright © 2006 IFAC*

Keywords: automotive applications, active front steering, functional safety, sensor failures, change detection, CUSUM, GMA, direct thresholding.

1. INTRODUCTION AND MOTIVATION

Active front steering is a newly developed mechatronic steering system for passenger cars that realizes an electronically controlled superposition of an angle to the hand steering wheel angle that is prescribed by the driver, cf. (Reinelt et al. 2004).

A great deal of the functionality that is housed in the electronic control unit is devoted to ensure the overall functional safety of the system, comprising mechanics, electronics and software. This paper will focus on safety measures that are required to reach the safety integrity level of the sensor measuring the position of the steering wheel. Beyond usual sensor diagnosis such as analogue signal monitoring, test patterns etc (all of them described in recognized safety standards such as (IEC61508 1998)), more advanced methods aiming at analytical redundancy of the sensor are needed. For relateted works on advancced fault detection in automotive systems we refer to (Harter 2000, Knoop et al 1999, Schwarte and Isermann 2002).

One method is estimation of the steering wheel angle with a kinematic relation. Having this filter for estimating the signal at hand, one is usually left with a deviation between the estimate and sensor measurement because of unmodelled dynamics, parameter inaccuracy, drift etc. The less perfect the match between estimate and sensor signal, the higher the need for more advanced methods assessing this mismatch, called the residual in what follows. Generation and assessment of residuals are usually chosen with respect to a minimum number of false alarms (to ensure availability) and to a maximum amount of fault detections (to ensure system safety). Based on earlier works, a proper choice of assessment-methods that are applicable on a production type electronic control unit is the focus of this work. Examples of several methods will be presented, based on measurements in a prototype vehicle.

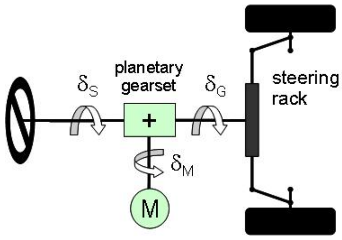

Fig. 1. Schematic view of active front steering. The electric motor superimposes an angle δ_M via a planetary gearbox to the hand steering wheel angle δ_S. The result is the steering gear's pinion angle δ_G.

Outline of the paper Sec. 2 establishes basic system description and notation. This is followed by a short background on functional safety in Sec. 3. The so called Angle Monitoring Algorithm that estimates the steering wheel angle is presented in Sec. 4. Change detection algorithms under investigation are compiled in Sec. 5 and some results from measurements done in a car are shown in Sec. 6 thereafter. We conclude in Sec. 7.

2. SYSTEM DESCRIPTION AND NOTATION

The complete active front steering setup including mathematical modelling and parameter estimation is described in (Klier and Reinelt 2004). In order to make this paper self-contained, the basic relations are given here as well. Fig. 1 shows the systems principle: The driver controls the vehicles course via the hand steering wheel; the resulting hand steering wheel angle is denoted by δ_S. Active front steering actuates an additional angle δ_M using its electric motor. Both angles result in a pinion angle δ_G down at the steering rack. All three angles relate as given in (1), also accounting for the respective ratios i_M, i_D. The resulting (average) road wheel angle can then be calculated via the pinion angle and a static nonlinearity $F_{SG}(\cdot)$ that accounts for the relation between pinion angle and rack displacement as well as for the steering geometry, cf. (2). Finally, the overall ratio between hand wheel to front road wheel $\delta_F(t)$ is defined in (3).

$$\delta_G(t) = \frac{1}{i_M} \cdot \delta_M(t) + \frac{1}{i_D} \cdot \delta_S(t) \qquad (1)$$

$$\delta_G(t) = F_{SG}\left(\delta_F(t)\right) \qquad (2)$$

$$\delta_F(t) = \frac{1}{i_V} \cdot \delta_S(t) \qquad (3)$$

Having this basic framework at hand, one can start looking at functions that manipulate the motor angle $\delta_M(t)$ in order to e.g. achieve a desired overall steering ratio i_V that depends on vehicle speed and pinion angle, i.e.:

$$i_V = i_V(v_X, \delta_G) \qquad (4)$$

This desired motor angle $\delta_{Md}(t)$ will then be passed to the motors feedback control algorithm. However, before designing such functions, the plausibility of all signals discussed so far has to be ensured, to ensure the safety of the system. This is part of the functional safety, described next.

3. FUNCTIONAL SAFETY

The so-called technical safety concept deals with ensuring the functional safety of the system, which means that no harmful actions are initiated (with a prescribed probability). The analysis process e.g. described in (Reinelt and Krautstrunk 2005) assigns a certain safety integrity level for each component in a top-down approach. Here, components can be actual devices such as sensors, microcontrollers, motors or functions (which are then mapped onto software modules). Having assigned a certain safety integrity level to a component, for example a sensor, a certain amount of safety measures has to be implemented until the risk reduction (as intended by the safety concept) is reached. Safety measures are usually classified as being *electrics/electronics dependent* or *application dependent*. The first category can be set up whenever the component in question is used – in any system. Examples are simple range and gradient checks of voltages that generate a sensor signal, watchdogs for microcontrollers etc. In safety standards such as (IEC61508 1998), the diagnostic coverage of these safety measures is low or medium, since they only represent necessary conditions for proper functionality. Hence, in systems of higher safety integrity level, they are accompanied by application dependent safety measures. These are based on application dependent relations. As an example, any of the sensors in the active front steering system could be validated exploiting (1) and assuming that the other two signals are valid. The information obtained from both types of safety functions is collected, the current state of the signals and the system is then assessed in the Failure Diagnosis and Management System (FDMS).

This contribution is concerned with the application dependent safety measures of the steering wheel angle sensor used in the active front steering system. In general, application dependent safety measures share a generic structure that is depicted in Fig. 2 and are already well established in literature (Basseville and Nikiforov 1993) and (Gustafsson 2000). The signal y_t [1], to be monitored, is compared to its estimate, generated for instance by a model also called *filter*. Most importantly, the filter has to use signals u_t that are inde-

[1] the notion (t) is used to indicate continues time signals while subscript t is used for discrete time ones.

Fig. 2. Generic structure of a safety measure containing filter, distance measure and stopping rule.

pendent of the signal to be estimated. The difference between signal and its estimate is called the *residual* ϵ_t. The *distance measure* then generates the *symptom* s_t. Finally, the *stopping rule* decides whether or not to raise an alarm. Usual stopping rules are direct thresholding, generalized moving average, cumulated sums etc, described in detail in Sec. 5. Mean, variance and other statistical properties could be used as distance measures. We refer also to (Gustafsson 2000) and (Basseville and Nikiforov 1993) for a state of the art overview of such techniques. Criteria for choosing one method over another are trade-off between mean time to detection and mean time to false alarm, but also re-usability, computational load etc.

4. ANGLE MONITORING ALGORITHM

The purpose of the Angle Monitoring Algorithm is to monitor the kinematic constraint (1) between the three angles in order to detect possible sensor failures of the steering wheel angle sensor, measuring $\delta_S(t)$. Although (1) looks quite simple, preliminary investigations show that it cannot be modelled in an acceptable accuracy as a linear black box model. The basic problem that prevents us from this approach is that the hand steering wheel sensor, measuring $\delta_S(t)$ is located in the top of the steering column, while the motor and pinion angle sensors are situated in the lower part of the steering column. A full multi-body model of the actuator is derived in (Klier and Reinelt 2004) and could contribute to overcome this problem. However, this model is not suited for implementation on a production type electronic control unit. Consequently, a simple solution has to be looked for: effects such as torsion of the steering column (which can be modelled in a linear fashion quite accurately) and effects of the universal joints in the steering column (which must be modelled using non-linear models) have been taken into account. All this leads to a linear black box model and a trailing static non-linearity, i.e. the following Wiener model:

$$\dot{x}(t) = Ax(t) + b(\delta_G^{\#}(t) - \delta_M^{\#}(t));\; x(0) = x_0 \quad (5)$$

$$\hat{\delta}_S(t) = J\left(Cx(t)\right) \quad (6)$$

where $\delta_G^{\#}(t), \delta_M^{\#}(t)$ are pinion and motor angle respectively, normalized to the hand steering wheel angle using (1). The LTI system (A, B, C) accounts for the linear torsion dynamics in (1) (basically using the steering velocity of the driver), and the static non-linearity $J(\cdot)$ accounts for possible effects given by universal joints in the steering column. Although an analytical expression for $J(\cdot)$ is at hand, it will not be possible to run it on the electronic control unit (from a computational point of view). Hence, a simplified – yet non-linear – version has been applied. The parameters have been identified and validated using measurements from a testbench and a prototype vehicle respectively, using standard identification methods (Ljung 1999) and (Milanese 1996) with a particular view on Wiener models, though, see (Bauer and Ninness 2002).

As pointed out earlier, the purpose of this algorithm is to detect sensor failures of the steering wheel angle sensor. The notion failure here refers to exceeding a certain deviation between measured and estimated angle over a certain time. The maximum allowed deviation, called $\delta_S^{\max}$, and the time range $T_S^{\max}$ are traced back from a system level specification down to the component.

5. MODEL-BASED FAULT DETECTION

Angle monitoring algorithm, as described in the last section, is used as filter to estimate the steering wheel angle ($y_t = \hat{\delta}_{S,t}$). Inputs u_t to the filter are the motor angle and the pinion angle, cf. Fig. 2. The difference between the estimated and the measured steering wheel angle is the residual and input to the distance measure:

$$\epsilon_t = \hat{\delta}_{S,t} - \delta_{S,t}. \quad (7)$$

A common approach to evaluate the residuals is to assume that the residuals resembles a white noise sequence with mean value zero and a known variance. When a failure occurs in the monitored signal it is assumed that the mean value of the residuals changes or the variance increases. Detecting such changes in signals is commonly known as change detection.

Both the CUSUM Test and the GMA test, which will be presented below, are based on the concept of the so called log-likelihood ratio, which is defined by:

$$s(\epsilon) = \ln \frac{p_{\theta_1}(\epsilon)}{p_{\theta_0}(\epsilon)} \quad (8)$$

where $p_{\theta_0}(\epsilon)$ is the probability density of the residuals before a failure and $p_{\theta_1}(\epsilon)$ is the probability density after, both depending on one scalar parameter θ. The log-likelihood ratio has one statistical property which is fundamental for detecting changes in signals:

$$E_{\theta_0}(s) < 0 \qquad \text{and} \qquad E_{\theta_1}(s) > 0 \tag{9}$$

or put in words, a change in the parameter θ is reflected as a change in the sign of the mean value of the log-likelihood ratio (Basseville and Nikiforov 1993).

5.1 *Cumulative Sum Test*

Consider the CUmulative SUM (CUSUM):

$$S_t = \sum_{i=1}^{t} s_i = \sum_{i=1}^{t} \ln \frac{p_{\theta_1}(\epsilon_i)}{p_{\theta_0}(\epsilon_i)}. \tag{10}$$

According to (9), S_t shows in average negative drift before a change in the parameter θ and positive thereafter. Therefore the difference between S_t and its current minimum value, $\mathrm{m}_t = \min_{1<j<t} S_j$, gives sufficient information about the change. Hence the following stopping rule is motivated:

$$g_t = \max(0, g_{t-1} + s_t) \tag{11}$$

and rise an alarm if g_t is greater than or equal to a threshold. To prevent positive drift before a change, which could cause false alarms, a drift-parameter ν can be subtracted, which gives the following form of the CUSUM Test (Gustafsson 2000):

$$g_t = \max(0, g_{t-1} + s_t - \nu) \tag{12}$$

and rise an alarm if g_t is greater than or equal to a threshold.

5.2 *Generalized Moving Average Test*

The generalized moving average (GMA) test is based on the behavior of the log-likelihood ratio (9). The idea is that in nonstationary situations it is of interest to use higher weights on recent observations and lower ones on past ones (Basseville and Nikiforov 1993):

$$g_t = \sum_{i=0}^{\infty} \gamma_i s_{t-i} \tag{13}$$

where $\gamma_i = \alpha(1-\alpha), 0 < \alpha < 1$ and s_i is defined in (10). α is usually referred to as the forgetting factor. This can be written in recursive form and gives the following stopping rule:

$$g_t = (1-\alpha)g_{t-1} + \alpha s_t \tag{14}$$

and rise an alarm if g_t is greater than or equal to a threshold.

5.3 *Direct Thresholding*

A simple stopping rule could be $\epsilon_t > \eta$, where $\eta > 0$ is a given threshold. This deviation could be allowed for a certain time interval, for example five consecutive sampling steps. A disadvantage of this direct thresholding approach is that no assumptions are made on the nature of the failure, hence the observer has to cope with all (possible or not) types of failures at any time.

5.4 *Summary of the Methods and Connection to Earlier Works*

Sensor failures follow common patterns very often. Switching bits are examples in digital sensors and offset or drift (due to aging or temperature) are quite common patterns for analogue sensors. Given an analogue sensor and knowing that offset or drift are not captured by hardware, it is straightforward to model them directly into the filter; this has already been investigated in (Reinelt and Lundquist 2005).

The main difference between the direct thresholding (see Sec. 5.3) and CUSUM and GMA (see Secs. 5.1 and 5.2) is that the latter ones process the physical information (deviation between sensed and estimated signal) over a time window. The first one transforms the physical information to a binary one (failure yes/no) before assessing this over time. This implies that maximum allowed deviation $\delta_S^{\max}$ and time range $T_S^{\max}$ as specified in the end of Sec. 4 have to be chosen as thresholds for the direct thresholding. In turn this means that the accuracy of the filter has to be better than this threshold in all faultless situations: $|\delta_{S,t} - \hat{\delta}_{S,t}| < \delta_S^{\max}$, in order not to generate any false alarm. A major motivation for using more advanced fault/change detection algorithms is that they can cope with less accurate filters without necessarily generating false alarms, as long as the statistical properties of the residuals ϵ_t are correct.

6. EXPERIMENTAL RESULTS

Below results from two different driving situations done with a prototype vehicle are presented. The Angle Monitoring Algorithm was used to estimate the steering wheel angle. The parameters of CUSUM and GMA were adjusted to detect relevant failures in the sensor signal and simultaneously minimize the number of false alarms. The parameters for direct thresholding were directly taken from the specifications $\delta_S^{\max}, T_S^{\max}$ as explained above.

In Fig. 3 the steering wheel angle, the estimated steering wheel angle (both in degrees) and the residual for the first driving situation are shown. At time 10s a step of size 10 degrees is added to the steering wheel angle. In Fig. 4 the outputs of CUSUM and GMA are shown. As it can be seen the fault is detected almost immediately.

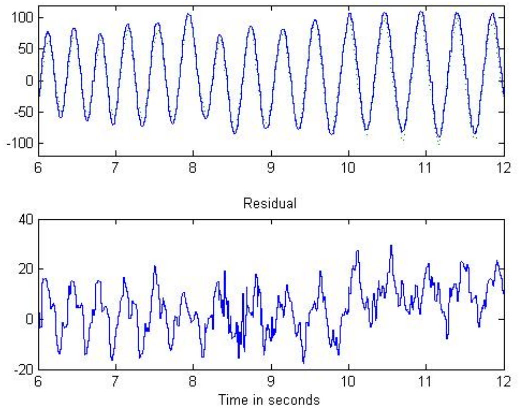

Fig. 3. Top: hand steering wheel angle (blue, solid) and estimated hand steering wheel angle (green, dotted). Bottom: residual. At time 10s a step of size 10 degrees is added to the hand steering wheel angle.

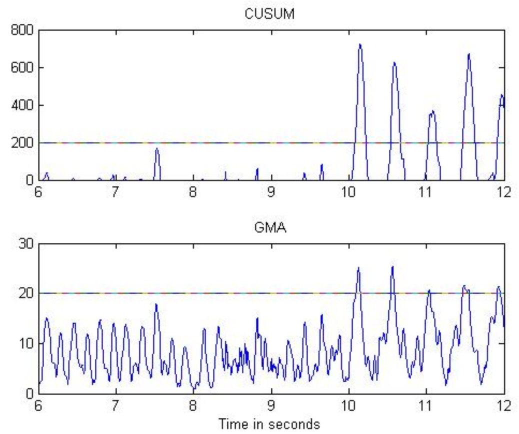

Fig. 4. As can be seen both CUSUM (top) and GMA (bottom) detects the failure depicted in Fig. 3 almost immediately.

In Fig. 5 the steering wheel angle, the estimated steering wheel angle (both in degrees) and the residual for the second driving situation are shown. At time 5s a ramp (3°/s) is added to the steering wheel angle. In Fig. 6 the outputs of CUSUM and GMA are shown. The fault is detected when the size has approximately grown to 19°. Generally it can be said that abrupt changes are detected faster and with smaller amplitude.

Although the residuals in Fig. 3 and 5 aren't white noise sequences (due to modelling issues), the results shows that the methods used still works, even though the statistical assumption made about the residuals aren't fully true.

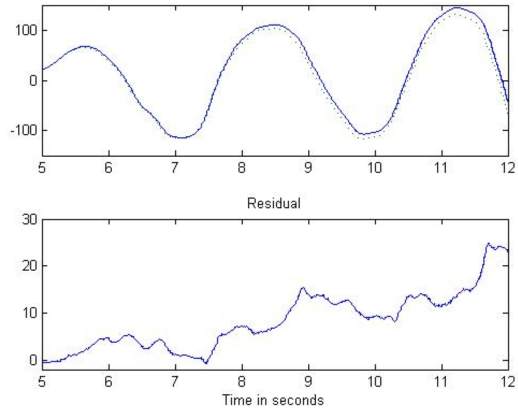

Fig. 5. Top:Hand steering wheel angle (blue, solid) and estimated hand steering wheel angle (green, dotted). Bottom: residual. At time 5s a ramp is added to the hand steering wheel angle (3°/s).

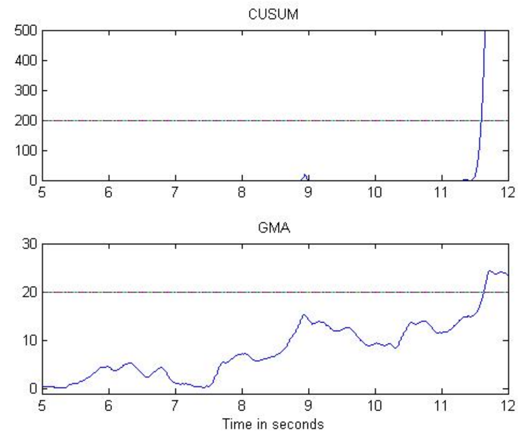

Fig. 6. As can be seen both CUSUM (top) and GMA (bottom) detects the failure depicted in Fig. 5.

The results from direct thresholding are not shown since the accuracy of the Angle Monitoring Algorithm is well above the specified failure thresholds and hence this method creates a great number of false alarms.

7. CONCLUSIONS AND FUTURE WORK

The so-called Angle Monitoring Algorithm that checks the kinematic relation of the active front steering system has been accompanied by distance measure and stopping rule in order to assess the residual, generated by the filter as deviation between estimated and measured steering wheel angle. Sample results from a prototype vehicle showed sufficient performance. In comparison to direct thresholding, angle failures of about half the magnitude can be detected with the change detection algorithms, without generating more false alarms. The algorithms presented are suited for production type of electronic control units with respect to their computational load.

Future work will concentrate on investigating other applications for these change detection algorithms in the active front steering system and determining the parameters with statistical methods. Another area of interest is to use observer based sensor monitoring as filter and to directly connect them to the distance measure and the stopping rule.

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