OBSERVER BASED SENSOR MONITORING IN AN ACTIVE FRONT STEERING SYSTEM USING EXPLICIT SENSOR FAILURE MODELLING

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Abstract: Active front steering is an emerging steering technology for passenger cars that realises 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 behaviour). In particular, observers are derived for estimating the position of the electric motor, used in the active front steering system as an actuator. These observers are accompanied by common failure patterns such as drift or offset in the sensors. Sample measurements from a prototype vehicle are presented.

Keywords: Brushless DC motor, sensor failures, fault detection, Luenberger observer.

1. INTRODUCTION AND MOTIVATION

Active front steering is a newly developed mechatronic steering system for passenger cars that realises an electronically controlled superposition of an angle to the hand steering wheel angle that is prescribed by the driver.

A great deal of 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 needed to reach the safety integrity level of the sensor, measuring the position of the electric motor. Beyond usual sensor diagnosis such as analogue signal monitoring, test patterns etc (all of them described in recognised safety standards such as (IEC61508, 1998)), more advanced methods aiming at analytical redundancy of the sensor are needed.

One method used within active front steering is estimation of the electric motor's position using Luenberger observers or (extended) Kalman filters. Starting off with a motor model, motor position or speed can be estimated using observer techniques (measuring voltages and currents of the motor). Given a sufficient overall tracking performance and accuracy of the filter, it is useful to directly model typical sensor failures such as offset or drift, as derived in a failure modes and effects analysis (FMEA). Doing so, the failure detection and management system (FDMS) can directly cope with these effects.

Applicability for production type electronic control units is discussed and accompanied by measurements from a prototype vehicle equipped with active front steering.

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. Models for the motor under investigation are compiled in Sec. 4 and some results of a Luenberger observer with respect to tracking and accuracy are shown in Sec. 5 thereafter. Sec. 6 then describes how to incorporate typical sensor failures and gives some results. We conclude in Sec. 7.

2. SYSTEM DESCRIPTION AND NOTATION

The complete system setup including mathematical modelling and parameter estimation is described in great detail 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 system's principle: The driver controls the vehicles

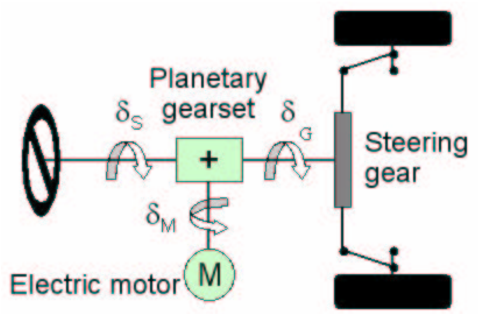

Fig. 1. Schematic view of active front steering. The electric motor superimposes an angle δ_M via a plantetary gerabox to the hand steering wheel angle δ_S. The result is the steering gear's pinion angle δ_G.

course via the hand steering wheel; the resulting 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 an 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).

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

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

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

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.:

$$i_V = i_V(v_X, \delta_G) \tag{4}$$

This desired motor angle $\delta_{Md}(t)$ will then be passed to the motor's 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 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 in place – 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 assessed in the Failure Diagnosis and Management System (FDMS).

This contribution is concerned with the application dependent safety measures of the motor angle sensor used the active front steering system. In general, application dependent safety measures share a generic structure that is depicted in Fig. 2 and already well established in literature (Gustafsson, 2000; Schwarte and Isermann, 2002). The signal or state $y(t)$, 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 independent of the signal to be estimated. The difference between signal and its estimate is called *residuum* $\epsilon(t)$. 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, generalised moving average, cumulated sums etc. Mean, variance and other statistical properties could be used as distance measures. We refer to (Gustafsson, 2000; Basseville and Nikiforov, 1993; Blanke et.al., 2003) for a state of the art overview of such techniques. Criteria for chosing one method over another are the trade-off between mean time to detection and mean time to false alarm, but also computational load etc.

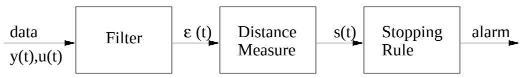

Fig. 2. Generic structure of a safety measure containing filter, distance measure and stopping rule.

4. MODELS OF THE BRUSHLESS DC MOTOR

Fig. 3 shows a brushless DC (BLDC) motor as used in the active front steering system including the different co-ordinate transformations and the current controller, realised in rotor (d, q) co-ordinates. Phase currents I_U, I_V, I_W of the BLDC motor are measured. These phase currents are transformed to stator (α, β) co-ordinates using the so-called *Clarke Transform*. Aiming at an *time invariant* co-ordinate system, they are transformed to (d, q) co-ordinates using the so-called *Park Transform*, cf. (Krause and Wasynczk, 1989).

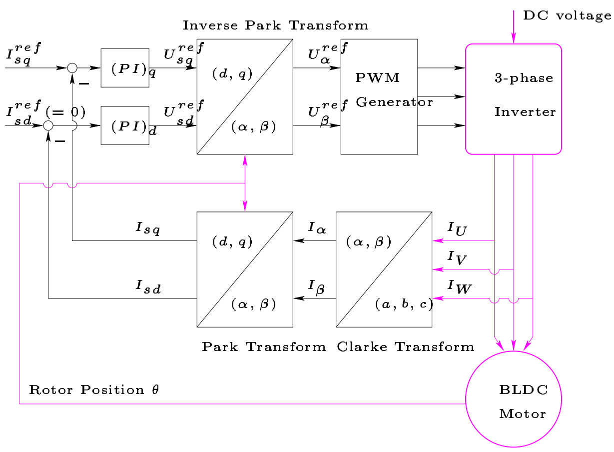

Fig. 3. Park/Clarke Transforms and Generation of PWM Signals.

The dynamics of the BLDC motor in (d, q) co-ordinates is given by (Krause and Wasynczk, 1989):

$$L_{sq}\dot{I}_{sq} = -L_{sd}z_p\dot{\theta}I_{sd} - c_M\dot{\theta} - R_sI_{sq} + U_{sq} \quad (5)$$

$$L_{sd}\dot{I}_{sd} = L_{sq}z_p\dot{\theta}I_{sq} - R_sI_{sd} + U_{sd} \quad (6)$$

$$J_M\ddot{\theta} = -b_M\dot{\theta} + c_MI_{sq} - M_{load}, \quad (7)$$

where z_p denotes the number of pole pairs, Ψ_p the rotor flux and $c_M = z_p \cdot \Psi_p$ the machine constant, R_s, L_s the resistance and inductance respectively. J_M is the moment of inertia, b_M the internal friction and finally M_{load} the external load. Obviously, this is a non-linear differential equation with the two electrical states I_{sd}, I_{sq} and the one mechanical state $\dot{\theta}$. When neglecting the sd component (i.e. $I_{sd} = 0$), or, equivalently, starting off with a simple DC motor to model the BLDC motor's dynamics, we obtain (with appropriate initial conditions):

$$L_{sq}\dot{I}_{sq} = -R_sI_{sq} - c_M\dot{\theta} + U_{sq} \quad (8)$$

$$J_M\ddot{\theta} = c_MI_{sq} - b_M\dot{\theta} - M_{load}. \quad (9)$$

The output signal is, in both cases, the current. Clearly, the rotor position can be chosen as output of the system, which implies adding this also as an extra state. Note, however, that this would not add extra parameters to the model.

Since the models contain a lot of physical parameters, these have to be estimated and validated from data. The parameters then are estimated with e.g. prediction error methods, see (Ljung, 1999) or unknown-but-bounded approaches (Milanese et.al., 1996), including parameter validation on validation data and a final assessment of the parameter quality. An overview and comparison of recent methods is given by (Reinelt et.al., 2002).

5. STATE ESTIMATION

5.1 Luenberger Observer

Consider the linear equations (8,9) written down in standard state space notation and neglecting the load input, i.e.:

$$\dot{x}(t) = \begin{pmatrix} -\frac{R_s}{L_{sq}} & -\frac{c_M}{L_{sq}} \\ \frac{c_M}{J_m} & -\frac{b_m}{J_m} \end{pmatrix} x(t) + \begin{pmatrix} \frac{1}{L_{sq}} \\ 0 \end{pmatrix} U_{sq}; x(0) = x_0 \quad (10)$$

$$y(t) = \begin{pmatrix} 1 & 0 \end{pmatrix} x(t) \qquad \text{with} \qquad x(t) = \begin{pmatrix} I_{sq}(t) \\ \dot{\theta}(t) \end{pmatrix} \quad (11)$$

or shorter:

$$\dot{x}(t) = Ax(t) + Bu(t); \qquad x(0) = x_0 \tag{12}$$
$$y(t) = Cx(t). \tag{13}$$

Since this is an observable linear model, an estimate $\hat{x}(t)$ of the state vector $x(t)$ can be calculated using a Luenberger observer that measures output $y(t)$ and input $u(t)$:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K\big[y(t) - C\hat{x}(t)\big]. \tag{14}$$

The error between real and estimated state vector $e(t) := x(t) - \hat{x}(t)$ tends to zero whenever the observer gain K is chosen properly, i.e. the system matrix $A - KC$ of the differential equation for the error

$$\dot{e}(t) = (A - KC)\, e(t); \qquad e(0) = e_0 \tag{15}$$

has eigenvalues in the left half plane. Based on the linear motor model in (d, q) co-ordinates (8,9), the Luenberger observer (14) is the first means to estimate the motor speed $\dot{\theta}(t)$ (and hence the position) based on measurements of currents and voltages.

5.2 Reduced Luenberger Observer

Since the current $I_{sq}(t)$ is state variable and (measured) output at the same time, it is not necessary to estimate it. Hence, the observer can be reduced to a one that only estimates the unknown state $\dot{\theta}(t)$. Therefore, the system is rewritten to (omitting the time argument t from now on):

$$\begin{pmatrix} \dot{y} \\ \dot{x}_2 \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \begin{pmatrix} y \\ x_2 \end{pmatrix} + \begin{pmatrix} B_1 \\ B_2 \end{pmatrix} U_{sq} \tag{16}$$
$$y = \begin{pmatrix} 1 & 0 \end{pmatrix} x. \tag{17}$$

The estimated value is x_2 and $x_1 = y$ is measured. Introducing new signals

$$u_r = A_{21}y + B_2U_{sq} \tag{18}$$
$$y_r = \dot{y} - A_{11}y - B_1U_{sq} \tag{19}$$

and new matrices $A_r = A_{22}$, $B_r = 1$, $C_r = A_{12}$, (16,17) become

$$\dot{x}_2 = A_r x_2 + B_r u_r \tag{20}$$
$$y_r = C_r x_2 \tag{21}$$

representing a system with a non-measurable state $x_2 = \dot{\theta}$. For this system, the Luenberger observer (as above) is:

$$\dot{\hat{x}}_2 = (A_r - K_rC_r)\,\hat{x}_2 + B_ru_r + K_ry_r \tag{22}$$

using K_r for the observer gain to be chosen. Resorting to the notation of (8,9) and introducing the new state $x_B = \dot{\hat{x}}_2 - K_ry$ yields the reduced observer for this case:

$$\dot{x}_B = \left(-\frac{b_m}{J_m} + \frac{c_M}{L_{sq}}\right)\hat{x}_B + \frac{K_r}{L_{sq}}U_{sq} + \tag{23}$$
$$\left(\left(\frac{c_M}{L_{sq}} - \frac{b_m}{J_m}\right)K_r + \frac{c_M}{J_m} + \frac{z_pR_s}{L_{sq}}\right)I_{sq}$$
$$\dot{\hat{x}}_2 = x_B + K_rI_{sq}. \tag{24}$$

Based on the linear motor model in (d, q) co-ordinates (8,9), the reduced Luenberger observer (23,24) is the second means to estimate the motor speed $\dot{\theta}(t)$ (and hence the position) based on measurements of currents and voltages.

5.3 Experimental Results

Figs. 4 and 5 show representative measurements from a vehicle equipped with active front steering. Two sample results have been chose, one for medium motor speeds and one for higher motor speeds. Preliminary investigations showed that there is no paramount difference between the Luenberger and the reduced Luenberger observer in terms of tracking and accuracy, hence we only show the results of the Luenberger observer. The algorithm has been executed using a dSpace device, which has also been used for storing the data. Devices for measuring motor voltages, currents and position are regular production type ones.

Computational load as well as a comparison with two other methods, namely an Extended Kalman Filter and a simple feedforward model in (α, β) stator co-ordinates is outlined in (Reinelt et.al., 2005).

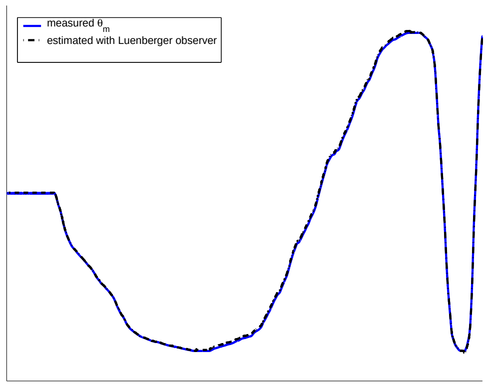

Fig. 4. Measurements in a protoype vehicle showing measured motor angle (blue, solid) and the estimate by the Luenberger observer (black, dashed) in a manoeuver that requires moderate speeds of the electric motor.

6. EXPLICIT FAILURE MODELLING

The observers presented in Sec. 5 aim at estimating the motor position as good as possible. during the fault detection process, the estimate

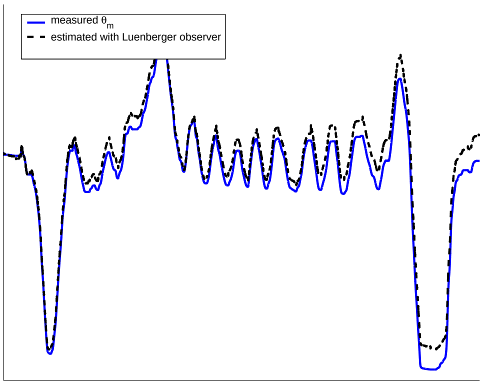

Fig. 5. Measurements in a protoype vehicle showing measured motor angle (blue, solid) and the estimate by the Luenberger observer (black, dashed) in a manoeuver that requires faster speeds of the electric motor.

would then be compared to the sensor signal, cf. also Fig. 2. A simple process for the fault detection scheme would be

$$\epsilon(t) = s(t) = |\theta - \hat{\theta}|,$$

and the stopping rule could be $\epsilon(t) > T$, where $T > 0$ is a given threshold. A disadvantage in this 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. But 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. According to (Gustafsson, 2000), offsets and drifts can be described as follows. A simple model for a (constant) offset m is $\dot{m} = 0$. This could then be added as an offset of the measured current I_{sq} to (10,11) as follows:

$$\dot{x}_o(t) = \begin{pmatrix} -\frac{R_s}{L_{sq}} & -\frac{c_M}{L_{sq}} & 0 \\ \frac{c_M}{J_m} & -\frac{b_m}{J_m} & 0 \\ 0 & 0 & 0 \end{pmatrix} x_o(t) + \begin{pmatrix} \frac{U_{sq}}{L_{sq}} \\ 0 \\ 0 \end{pmatrix} \quad (25)$$

$$y(t) = \begin{pmatrix} 1 & 0 & 1 \end{pmatrix} x_o(t), \; x_o(t) = \begin{pmatrix} I_{sq}(t) \\ \dot{\theta}(t) \\ m(t) \end{pmatrix}. \quad (26)$$

Quite similar, a drift d of the measured current I_{sq} to (10,11) as follows:

$$\dot{x}_d(t) = \begin{pmatrix} -\frac{R_s}{L_{sq}} & -\frac{c_M}{L_{sq}} & 0 & 0 \\ \frac{c_M}{J_m} & -\frac{b_m}{J_m} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix} x_d(t) + \begin{pmatrix} \frac{U_{sq}}{L_{sq}} \\ 0 \\ 0 \\ 0 \end{pmatrix} \quad (27)$$

$$y(t) = \begin{pmatrix} 1 & 0 & 1 & 0 \end{pmatrix} x_d(t), \; x_d(t) = \begin{pmatrix} I_{sq}(t) \\ \dot{\theta}(t) \\ d(t) \\ c(t) \end{pmatrix}. \quad (28)$$

Doing so, offsets and drifts (or both) of the current measurement can be estimated quite straightforwardly. Once for instance an offset is established, the sensor signal could be corrected accordingly for the next drive cycle. Fig. 6 shows an example. There, a drift in the motor current is simulated. While the observer with explicit offset and drift modelling still estimates the position quite well, the estimate of the obeserver *without* explicit failure modelling tends to follow the drift.

In the same way, a drifting measured voltage $U_{sq} + d$ can be modelled as follows:

$$\dot{x}_d(t) = \begin{pmatrix} -\frac{R_s}{L_{sq}} & -\frac{c_M}{L_{sq}} & 0 & 0 \\ \frac{c_M}{J_m} & -\frac{b_m}{J_m} & \frac{1}{L_{sq}} & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{pmatrix} x_d(t) + \begin{pmatrix} \frac{U_{sq}}{L_{sq}} \\ 0 \\ 0 \\ 0 \end{pmatrix} \quad (29)$$

$$y(t) = \begin{pmatrix} 1 & 0 & 0 & 0 \end{pmatrix} x_d(t), \; x_d(t) = \begin{pmatrix} I_{sq}(t) \\ \dot{\theta}(t) \\ d(t) \\ c(t) \end{pmatrix}. \quad (30)$$

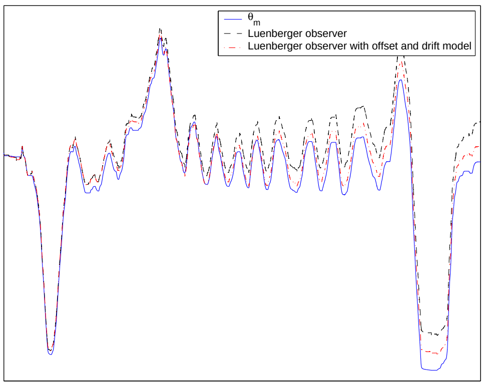

Fig. 6. Measurements in a protoype vehicle showing measured current I_{sq} (blue, solid) with a drift in the measured current arising as $10s$, the estimate by the Luenberger observer (black, dashed) and the estimate by the Luenberger observer using a drift and offset model (red, dash-dotted).

7. CONCLUSIONS AND FUTURE WORK

Observers as well as reduced state observers have been derived for estimating the postion of the electric motor, used in the active front steering system. The models used for building the observers have been accompanied by common failure patterns such as drift or offset in the senors. Sample measurements from a prototype vehicle showed sufficient performance. The algorithm needs to run the linear motor model plus the update of the state vector at each sampling instance, which is computationally quite cheap (counting the number of floating point multiplications). Adding explicit failure models generates extra states, but the resulting state space representatin tends to be sparse, adding not much computational burden to the algorithm. Overall, the algorithms presented are suited for production type of electronic control units.

Future work will concentrate on investigating temperature dependence of the model and running the observers on a production type electronic control unit using automated code generation. More sophisticated failure models, directly derived in a failure modes and effects analysis will be incorporated into the motor model as well.

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