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Centralized Monitoring for Vehicle Dynamics Sensor Networks

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Abstract: An increasing number of control systems in modern automotive vehicles is based on measurements of signals describing vehicle dynamics. Correspondingly, a large number of sensors is required. To spare on weight and even more important on costs, car manufacturers require joint processing of sensors, i.e. the individual sensors related to certain control systems should become part of a sensor network. In the paper at hand the possibilities and shortcomings of such an approach are examined from a sensor monitoring and estimation perspective. Especially, redundant and model based failure detection are considered. The focus is on signals and sensors related to vehicle dynamics and the corresponding question of fall back strategies in case of sensor failure. Corresponding problems are addressed with the introduction of a new sensor network architecture.

1. INTRODUCTION

Starting with the ABS system (anti lock braking system) more than 25 years ago, the number of vehicle control systems is still increasing. These systems are typically based on sensor information and the sensors in turn have to be supervised in order to guarantee correct system performance. This is especially true for safety critical systems, i.e. systems that actively influence vehicle movement.

Typical examples are all restraint systems (airbags), active front steering (AFS), and VDC systems (vehicle dynamics control systems van Zanten et al. [1998]). These examples have in common that the main functionality is based on signals related to vehicle dynamics. Furthermore, these systems together comprise almost all relevant sensor signals from vehicle dynamics and therefore are considered as the basis for the following discussion.

1.1 Considered Control Systems

VDC systems use signals to derive the drivers intent (steering wheel angle, brake pressure, engine torque). Based on a comparison with the actual vehicle motion (yaw rate, lateral acceleration, velocity) corrective actions by means of controlled braking of individual wheels can be initiated by the system. Since this intervention is safety critical, the underlying measurements related to lateral dynamics (i.e. steering wheel angle, yaw rate, and lateral acceleration) closely have to be monitored for possible faults van Zanten [2006].

AFS systems can actively influence the steering angle at the wheels. A typical technical realization is a planetary gear set inserted in the steering linkage. The system action again depends on the actual vehicle motion (yaw rate, lateral acceleration, velocity). Clearly also in this case erroneous system action due to sensor faults must be avoided.

Restraint systems differ from the previous mentioned systems in the sense that they are only active once, i.e in case of an accident. However, sensor faults with the consequence of airbag activation at the wrong time surely must be detected. Airbag activation due to collisions requires fast acceleration sensors (typical sampling rate: 1 ms) with data transmission on special buses. Therefore joint processing with the comparatively slow systems VDC and AFS ($10 - 20$ ms sampling rate) is not possible.

Here, we consider second generation restraint systems aiming at rollover accidents (ROS - rollover systems). The scope of the associated curtain airbag is to take care of that the occupants stay inside the vehicle in course of a rollover accident. Necessary sensor information are lateral (a_y) and vertical (a_z) acceleration and the roll rate ω_x (for details see Kröninger et al. [2004]). For this system the corresponding dynamics and also the rage of the used sensors is compatible to AFS and VDC systems.

1.2 Combined Sensor Monitoring and Signal Estimation

Functional benefits by combination of vehicle control systems is considered in Schwarz [2006]. Here, the potential for sensor monitoring and estimation is examined. Having more than one of the mentioned systems available implies redundancy either for the yaw rate sensor (ω_z) or the lateral acceleration sensor (a_y). Although from a technical point of view sensors could be spared in these situations, this option is not realized up till now due to liability concerns of the possibly different manufacturers of the considered control systems.

Joint processing of sensor signals is an alternative to provide some additional functionality. Sensor redundancy, for example, offers the possibility of fast failure detection (see Hillenbrand et al. [2007] for an application in vehicle dynamics monitoring). Furthermore enhanced model based supervision and better signal estimation is possible if a variety of sensor signals is available. A detailed discussion of possible benefits is given in Rehm and Hofmann [2004].

The corresponding algorithms are in principle known (see Ding et al. [2004], Halbe [2007] for supervision and Kiencke and Nielsen [2000], Hillenbrand et al. [2007] for estimation). New is the question what happens if these algorithms are combined within a sensor signal processing network.

As an example consider velocity estimation: vehicle velocity is essential for model based monitoring of the yaw rate. However, the yaw rate is needed to estimate velocity. This circular reasoning surely has to be avoided in a central sensor processing unit (CSPU). This point is examined in the following section.

Although central sensor signal processing has clear advantages, there also is a drawback, namely the indirect coupling of the systems using estimated or supervised signals from the CSPU. Especially the question of fall back strategies in the case of a detected failure is open. Clearly not all systems should shut down in this case. This point is addressed by the introduction of an hierarchical architecture for a CSPU in the third section of the paper at hand.

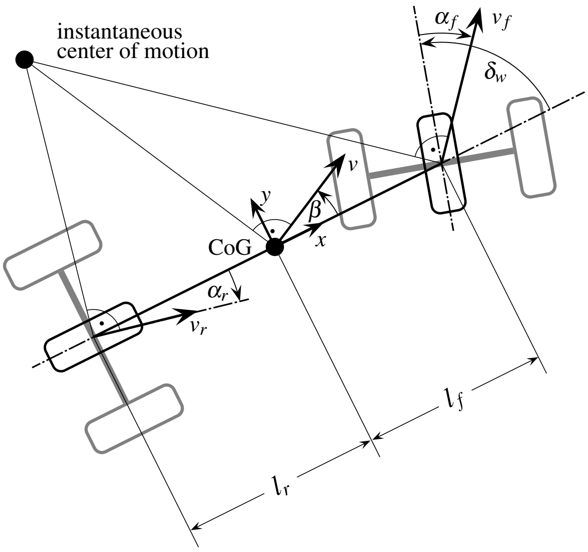

Fig. 1. Scheme of the single track model.

2. ANALYSIS OF SUPERVISION ALGORITHMS

In this section we examine the logic behind model based failure detection for vehicle dynamics sensors. The employed models are based on the single track model Wong [2001]. Relevant parameters and the idea of a simplification towards a single track model is depicted in in Figure 1.

As a minimal sensor basis of a CSPU we consider the sensors used by a VDC system. This assumption is based on the fact that these system are almost standard in upper-middle-class vehicles (in Europe). The corresponding sensors are wheel turn rates (ω_i, $i = 1(1)4$), steering wheel angle (δ_S), lateral acceleration (a_y), and yaw rate (ω_z). The angle at the front wheels δ_R can be computed from the transmission of the steering linkage ($\delta_S = i_S \delta_R$ with constant transmission factor i_S), or is available from an AFS system. Vehicle velocity v is estimated in the VDC system with a Kalman filter on the basis of the mentioned signals and further inputs from the motor management van Zanten et al. [1998].

The main problem of model based supervision in vehicle dynamics is that the employed models typically are not valid in all driving situations. Especially the following models for δ_S, a_y, ω_z are not valid if the side slip angle β (angle of the velocity vector with respect to the longitudinal axis of the vehicle, see Fig. 1) or the rate of change $\dot{\beta}$ are not “small” (typical situation: skidding). The corresponding driving situations are termed *unstable* in the following.

Table 1. Supervision by means of single track model.

	residual 1: ω_z, δ_S	residual 2: a_y, δ_S	residual 3: a_y, ω_z
ω_z-sensor defect	x		x
a_y-sensor defect		x	x
δ_S-sensor defect	x	x	
tires saturated	x	x	
non-even road	x	x	x
vehicle unstable	x	x	x

Sensor monitoring typically includes three different layers Isermann [1997]. Model based supervision is considered the third layer. The first layer contains sensor build-in test procedures which basically check sensor hardware for failures Henry and Clarke [1993]. Signal-individual tests for signal plausibility (physical limits) and signal characteristics (e.g. periodicity or statistical properties) make up the second layer (see also Basseville and Nikiforov [1993]).

In context of the supervision of the VDC sensors we only consider the first layer for the wheel turn rates, i.e. for the model based supervision layer the ω_i are already cleared by tests on the hardware level. The reason is that their digital measurement principle is not affected by slowly growing offsets as it is the case for a_y and ω_z.

The following models are used for model based supervision of the remaining signals δ_S, a_y, and ω_z Ding et al. [2004].

(1) Relation between yaw rate and steering angle:

$$\delta_S = \frac{(l_V + l_H) \cdot i_s}{v} \omega_z \tag{1}$$

(2) Relation between lateral acceleration and steering angle:

$$\delta_S = \frac{(l_V + l_H) \cdot i_s}{v^2} a_y \tag{2}$$

(3) Relation between lateral acceleration and yaw rate:

$$a_y = v \omega_z \tag{3}$$

All three models require a horizontal road. Additionally the first and second model are based on the assumption of non-saturated tires (no combined lateral and longitudinal slip, maximal 30% use of the tire friction potential Pasterkamp [1997]).

A rather simple evaluation of model based fault detection can be realized based on logic tables where the effect of one sensor fault, ı.e the deviation form the model, is captured by certain fault indicators (termed residuals). The idea is that not every indicator is sensitive to every sensor fault. Thus a sensor fault identification is possible provided that the logic table is invertible and that it is appropriate to assume that only one fault may happen over some time interval.

The result for the model equations (1,2,3) is given in Table 1. The residual patterns show that an identification of an ω_z and a_y failure is possible while a δ_S failure cannot be separated from a non-valid model assumption. Note also that the velocity is assumed to be fault free. This implies that velocity estimation is possible without the information from δ_S, a_y, and ω_z. This will be an important point for the supervision architecture in the next section.

Since failure detection for the steering angle obviously is a problem, also the detection of failures based on the steering angle is questionable. Therefore kinematic relations are used to express a_y and ω_z in terms of the wheel turn rates ω_i. The result is given in Table 2.

Table 2. Supervision by means of wheel velocities.

	residual 1: $\omega_z(\omega_i)$	residual 2: $a_y(\omega_i)$	residual 3: a_y, ω_z
ω_z-sensor defect	x		x
a_y-sensor defect		x	x
non-even road		x	x
vehicle unstable	x	x	x
slip (longitudinal)	x	x	

In this case it is not possible to differentiate between a a_y failure and a non-valid model (road is not horizontal). The combination of both concepts leads to Table 3. Evidently there is no principle improvement with respect to failure detection. In practice fault detection based on wheel turn rates can be realized with faster detection rates than the single track model based approach.

Table 3. Supervision by means of wheel velocities

	res. 1: ω_z, δ_S	res. 2: a_y, δ_S	res. 3: a_y, ω_z	res. 4: $\omega_z(\omega_i)$	res. 5: $a_y(\omega_i)$
ω_z-sensor defect	x		x	x	
a_y-sensor defect		x	x		x
δ_S-sensor defect	x	x			
tires saturated	x	x			
non-even road	x	x	x		x
vehicle unstable	x	x	x	x	x
slip (longitudinal)				x	x

2.1 Invariant based approach

In Rehm and Otterbein [2005] a generalized single track model is considered. As one result it turns out that

$$\delta_S = i_S(l_V + l_H)\left(\frac{\omega_z}{v} + \frac{a_y}{v_c^2}\right) \tag{4}$$

holds independent from road inclination (v_c: characteristic velocity). However, stable driving is required, i.e. the previous assumptions for the side slip angle must hold true for (4) being valid. The idea to incorporate this formula into the supervision logic is not to supply further possibilities to differentiate sensor faults but to detect driving situations where the supervision models are in principle not valid. With (4) as basis for an additional residual one gets Table 4.

Table 4. Supervision with an invariant relation

	res. 1: ω_z, δ_S	res. 2: a_y, δ_S	res. 3: a_y, ω_z	res. 4. a_y, ω_z , δ_S
ω_z-sensor defect	x		x	x
a_y-sensor defect		x	x	x
δ_S-sensor defect	x	x		x
tires saturated	x	x		x
non-even road	x	x	x	
vehicle unstable	x	x	x	x

As expected it is still not possible to extract the information on a defect steering wheel sensor. However, it is now possible to distinct the case “non-even road” from unstable driving. This may be useful to reduce false alarm rates.

2.2 Additional Vehicle Control Systems: ROS system

In this case the VDC sensors are complemented by an additional a_y sensor and a roll rate sensor (ω_x). The a_y sensor can be used for redundant supervision, i.e. a deviation between the two sensor can be used to detect a fault. A subsequent comparison of the measured data with data from a model, e.g. Eq. (3) can be used to identify the faulty sensor (implementation details considering noise are given in Hillenbrand et al. [2007]). However, at this stage the required signals for (3) i.e. ω_z and v should already be checked as fault free.

The ω_x sensor allows for an estimation of the roll angle. One possibility is to combine a kinematic model (v_x longitudinal component of vehicle velocity v)

$$\omega_x = \frac{d}{dt}\left(\frac{a_y - \omega_z v_x}{g}\right) \tag{5}$$

with an identified linear second order model (input: a_y, output: roll angle, see also Hillenbrand et al. [2007]).

With this angle information we can explicitly characterize the “non-even road” condition (except for the minor problem of changing bank angles) and thus we might expect that an improvement with respect to monitoring within the VDC sensors is possible. However, Table 5 shows that this is not the case. Additional to the previous residuals, two residual (res. 5, res. 6) based on ω_x are introduced. Residual 5 is based on (5) and Residual 6 on the second order relation between roll angle and a_y. As before we cannot differentiate between steering angle failure and saturated tires. Unexpected is that is not possible anymore to detect a yaw rate failure since the corresponding residual pattern is the same as for unstable driving.

The reason for this unexpected behavior is that lifting the non-even road condition implies the usage of models replacing (1,2,3) with the angle information being included. Thus the corresponding residuals are also affected by an ω_x failure and in turn we have the residual patterns in Table 5. Also considering a two step approach for supervision does not alter this result. Thus the ω_x signal is not useful for supervision of the VDC signals a_y, δ_S, and ω_z. However, the estimated roll angle is of great interest for the VDC system since it allows for more adequate control action in case of vehicles with high center of mass.

Table 5. Supervision with estimated roll angle

	res. 1: ω_z, δ_S	res. 2: a_y, δ_S	res. 3: a_y, ω_z	res. 4: a_y, ω_z, δ_S	res. 5: ω_x, a_y, ω_z	res. 6: ω_x, a_y
ω_z-sensor defect	x	x	x	x	x	
a_y-sensor defect	x	x	x	x	x	x
δ_S-sensor defect	x	x		x		
ω_x-sensor defect	x	x	x		x	x
tires saturated	x	x		x		
bank angle not const.						x
vehicle unstable	x	x	x	x	x	

2.3 Additional Vehicle Control Systems: AFS system

With the AFS system we get additional possibilities for redundancy supervision, namely for a_y and ω_z. With respect to the δ_R sensor (angle of the front wheels) of the AFS system the situation is more subtle. This is no redundancy for the δ_S sensor of the VDC system, since direct linkage of the steering angle to the front wheels is interrupted in order to introduce the AFS control input.

3. FAULT DETECTION ARCHITECTURE

The previous section showed that the combination of vehicle dynamics sensor signals in a CSPU comprises model based supervision, supervision for redundant sensors, and model based estimation. Furthermore the need to supervise groups of signals (namely a_y, ω_z, δ_S) became clear. Suitable algorithms for these different tasks are known from the literature.

However, a suitable processing architecture is open. This architecture should fullfil three major requirements:

(1) No logical loops, i.e. supervision of a signal based on non-supervised input information.
(2) Maximal availability of supervised sensor information.
(3) Simple fall-back strategies in case of sensor failures.

We argue in the following that the concept given in Figure 2 meets these requirements.

We consider the systems VDC, AFS, ROS as before and additionally an a_x sensor (longitudinal acceleration) which is standard in all four-wheel drive vehicles. The corresponding sensors are shown on the left hand side of Figure 2. Signal processing is done “from left to right”.

The very first step is to provide a supervised velocity signal (v_{x0}). This is necessary since all subsequent models need velocity information. This supervised velocity signal can be derived from wheel turn rates (considered supervised a priori) although not with high accuracy van Zanten et al. [1998]. Better estimates are possible when additionally rigid body kinematics of the vehicle is taken into account. However, the corresponding transformations require ω_z and δ_S Kiencke and Nielsen [2000] which are not supervised at this point. The corresponding signal is computed in a subsequent level and termed v_x. One possible approach to estimate v_x is given in Imsland et al. [2005].

In the next step supervision based on redundancy is realized. In case of triple redundancy, detection and identification of the failure is directly possible Isermann [1997] otherwise a combination with model based techniques is necessary Hillenbrand et al. [2007]. A status flag indicates the quality of the supervised signals. If redundancy monitoring is successful a signal gets the maximal quality value at this point. If there are no multiple sensors for a signal the redundancy block is void.

Afterwards joint supervision of a_y, ω_z, δ_S is realized (e.g. Ding et al. [2005], Halbe [2007]). With supervised signals ω_z, δ_S available, it is possible to compute the higher quality velocity signal v_x. This signal can be used to validate a_x by means of numerical differentiation.

Furthermore, at this stage all signals necessary for signal estimation (lateral velocity, lateral and longitudinal road inclination) are available as supervised signals with inherited quality flags. In the same way, in case of an indicated failure, the corresponding information is inherited to all subsequent processing units .

Based on the quality flags indicating the status of supervision of a signal, it is possible for the vehicle systems to decide whether a secure function is possible or not.

Finally we remark that the proposed architecture is inherently modular in the sense that necessary changes in case of missing systems are immediately clear.

4. CONCLUSIONS

The supervision and estimation structure of sensors from vehicle dynamics within a central signal processing unit (CSPU) was examined.

It turned out that a joint treatment of certain groups of signals (especially velocity, steering wheel angle, yaw rate, and lateral acceleration) is mandatory in order to avoid “supervision loops”. These structural results led to an hierarchical architecture for such a CSPU. Two major problems are solved by this novel concept:

1. The requirement to include a *supervised* velocity signal in almost all algorithms for vehicle dynamics sensor monitoring is met by an gradual velocity estimation in two steps.

2. The question of fall-back strategies in case of sensor failures. A signal quality flag indicating the supervision status of a signal is updated in course of the hierarchical processing. In case of degradation all subsequent processing units relying on the respective signal adapt the quality flag information for their output signal.

Furthermore the modular structure of the proposed architecture allows for an easy extension in case of additional sensors.

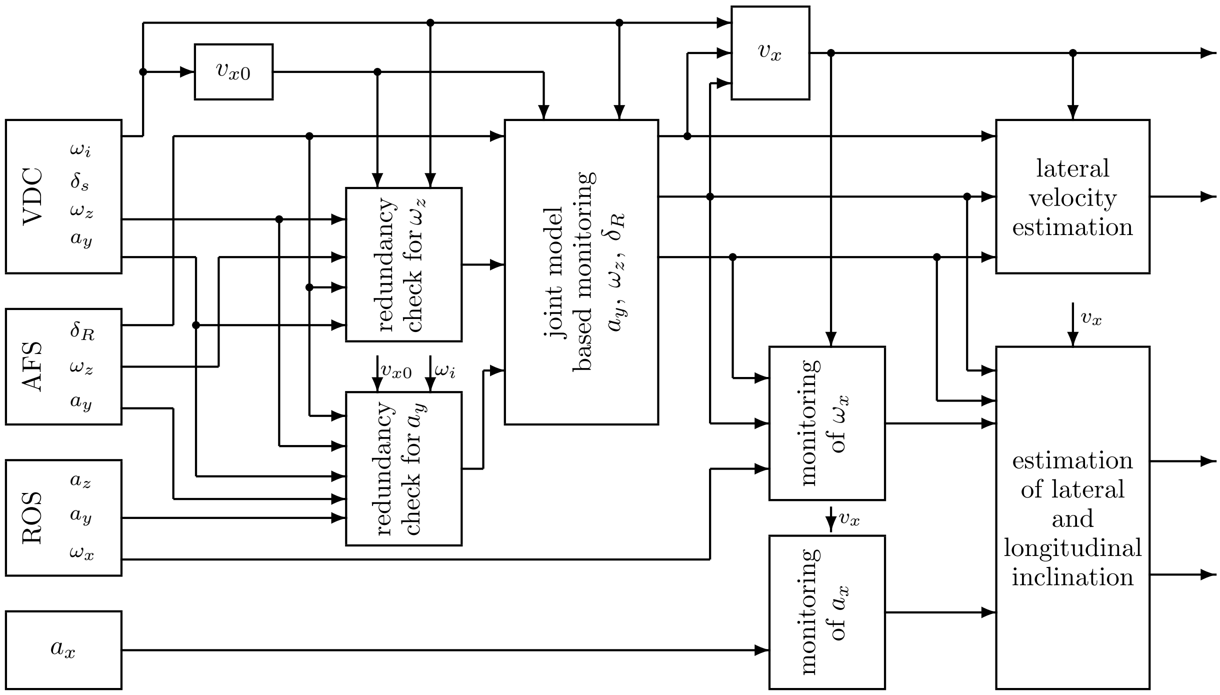

Fig. 2. Architecture for supervision and estimation

This open structure may not only be useful for the primary application (driver plus vehicle) but also as a structural sensor concept for the much larger sensor equipment in autonomous vehicles. Looking in the future, further applications may be sensor processing for vehicles in platoons or within the more general context of inter vehicle communication.

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