Plausibility Checking of Sensor Signals for Vehicle Dynamics Control Systems

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Latest technological developments have enabled the evolution of new vehicle systems which allow the implementation of new functions or the realisation of known functions with alternative actuation systems. The rising complexity of such systems seriously affects the safety demands on these systems. The following contribution describes a plausibility checking system and a method to define the requirements to plausibility checking systems in order to achieve required safety demands for new vehicle systems.

1. INTRODUCTION

Recent developments in the fields of smart semi conductor technology, electric drives like brushless DC motors, the performance increase of micro controller systems and the establishment of real-time data buses form a basis for the development of new automotive systems. The latest innovations on the market in the field of vehicle dynamics driven by this development are for example active front steering or torque vectoring systems. In the future, rear wheel steering, partial or full steer-by-wire, and global chassis control will complete this field, along with further developments. On one hand all these systems enable completely new possibilities of function development, on the other hand the realisation of established functions with alternative actuation systems become possible. These possibilities lead to a new dimension in complexity and safety criticality of the entire vehicle system. To satisfy the resulting safety demands, the design of the system must allow a maximum degree of system integrity.

Besides the possibilities of safe dimensioning of the systems' parts and components, robust control algorithms et cetera, plausibility checking procedures of sensor input signals are a key element in achieving the demanded degree of system integrity.

A similarly important fact is that the ability of repair shops to identify and locate faults in such complex systems is limited. This leads to the need for adequate on board or on-line diagnosis systems which allows proper service of such systems. Here again, the plausibility checking system delivers the input for the identification of defect system components, particularly in the context of sensor or wiring defects.

2. PLAUSIBILITY CHECKING SYSTEM

In order to guarantee the demanded system integrity, systems need to be fault tolerant, reliable and safe. To set up a fault tolerant system, it must be able to recognise faults sensible and fast. This is realized by the plausibility checking system proposed in this contribution. With the information about the reliability of incoming sensor and input signals, it enables the controller to take adequate error handling measures, depending on the safety relevance of the system and the severity of the fault.

The structure of the modular and scalable plausibility checking system developed at ika/fka for vehicle dynamics control systems is shown in Fig. 1. The system's modular composition and scalability allow for a wide range of possible applications: in its most simple form, the monitoring system is adequate for early stages of prototype system development, while in its most advanced set-up it satisfies the performance requirements necessary for series applications. Due to its adaptive design, the plausibility checking system's use is not limited to a specific type of vehicle dynamics control system, but can be adapted for brake systems (such as ESP – Electronic Stability Program), active steering systems, suspension control or any other system utilizing vehicle sensor inputs.

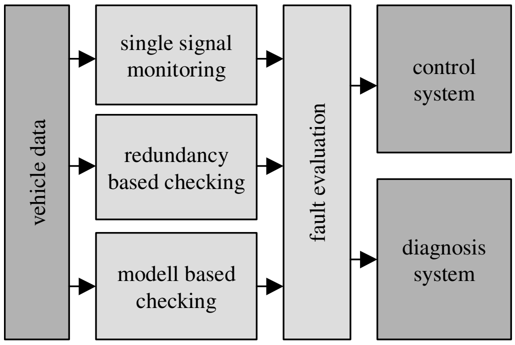

Fig. 1: 3-step plausibility checking system

The plausibility checking procedure presented in this contribution comprises three modules for observation and one module for combuined evaluation. Those are:

- single signal monitoring
- redundancy based plausibility checking
- model based plausibility checking
- fault evaluation

While single signal monitoring is applied to all signals observed, redundancy based checking is used for signals provided by two or more sources. Model based checking can be adopted where an analytical redundancy can be established. Which module is used for each signal greatly depends on the application and safety requrements.

In each observation module, integrity values are calculated on-line for each signal observed, representing the degree of signal plausibility according to the particular observation method. Depending on the module specifications, the integrity value for a signal can be increased (validation of the signal e.g., redundant sensors providing consistent values) or decreased (degradation of the signal e.g., conflicting values from redundant sensors).

The integrity values from all three observation modules are communicated to the fault evaluation module. The three values are summed up, providing the possibility to weigh the values differently according to the current driving situation. For each signal observed in the plausibility check, a level of signal integrity is determined. Finally, the fault pattern is analysed and corrupted data source are identified.

The results of the fault evaluation are provided to the control system and the diagnosis system for further processing. Depending on the severity of the fault and the necessity of the affected signal for the control task, partial disabling of certain functions or deactivation of the control system in a safe state can be induced.

2.1. Single Signal Monitoring

Firstly, all signals are examined independently in the single signal monitoring module. The single signal monitoring contains analyses of specified minimum and maximum values, signal gradients, and the examination of signal noise levels.

Fig. 2 shows the process of calculating the integrity value in this module. If the measured signal property (signal value, gradient, or noise level) does not exceed a specific lower threshold, the plausibility value of the signal is not affected. As soon as the property value exceeds the lower threshold, degradation is started. With the exceeding of the upper threshold, the single signal monitoring integrity value is maximally degraded, reaching its minimum value of minus one.

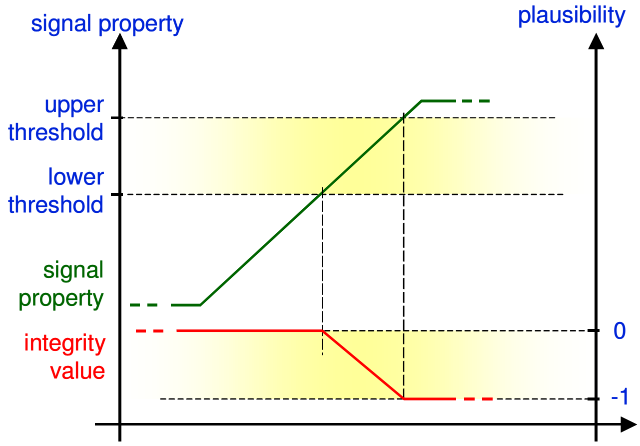

Fig. 2: Single signal monitoring: integrity value

The system is set up in a way that all calculated plausibility values are normalized to the value range from zero to one. This guaranties the comparability of the calculated plausibility vales through the entire system.

The example shown in Fig. 3 is generated from simulation results. It is assumed that a signal normally containing noise suddenly rises to a constant value within the valid range of values.

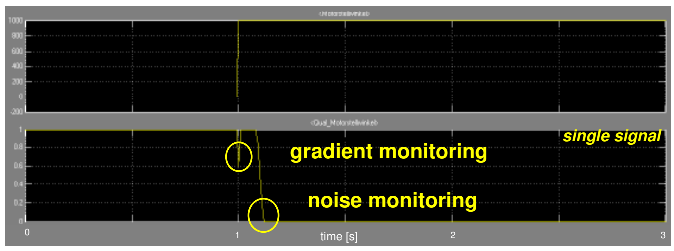

Fig. 3: Fault detection by single signal monitoring

During a short period, the integrity value of the signal is reduced due to gradient monitoring. When the signal reaches the constant value, the integrity value is increased again. Owing to the absence of noise in the corrupted signal, the noise monitoring algorithm is triggered, continuously degrading plausibility. After a timespan of approximately 100 ms, the signal defect is detected correctly.

Although this module can be applied to all possible signals, relatively large discrepancies between sensor signal and possible physical values are necessary in order to highlight implausibility. Therefore, this method is useful and necessary for basic signal observation, but not sufficient for meeting the requirements of fast and precise fault detection.

Due to its working principle, the single signal monitoring is only able to detect signal defects, thus leading to a degradation of a signal's plausibility if a fault is detected or leaving it neutral otherwise. Therefore, the margin between upper and lower threshold can be chosen very small, so the degradation takes place sufficiently fast.

2.2. Redundancy Based Plausibility Checking

In contrast to single signal monitoring, redundancy based plausibility checking provides a much higher potential in terms of detection time and precision. The redundancy based plausibility checking uses redundant sensor signals as far as available. The signals of redundant sensors are analyzed, and a plausibility value is generated from the difference between the signals. The clear drawback of this approach is the need for additional sensor equipment, which conflicts with the necessity for cost reduction in production vehicles.

Fig. 4. shows how the degradation of the plausibility value is calculated based on the deviation of the sensor values. It is assumed that a pair of sensors always delivers signals with a certain deviation. Reasons for this are signal noise, manufacturing tolerances and deviation caused by the mounting of the sensors inside the vehicle. Because of this, the value for the threshold is chosen in this set-up in a way that the half threshold coincides with the expected deviation while proper operation of the sensors. If now the deviation between the sensor signals becomes grater than half of the threshold, the degradation begins. The degradation reaches its maximum when the deviation value is equal to the threshold. If the deviation between the sensor signals is less than the expected deviation, this is an indicator for enhanced reliability of the sensor signals and the plausibility value can be increased, leading to an additional validation of the signal.

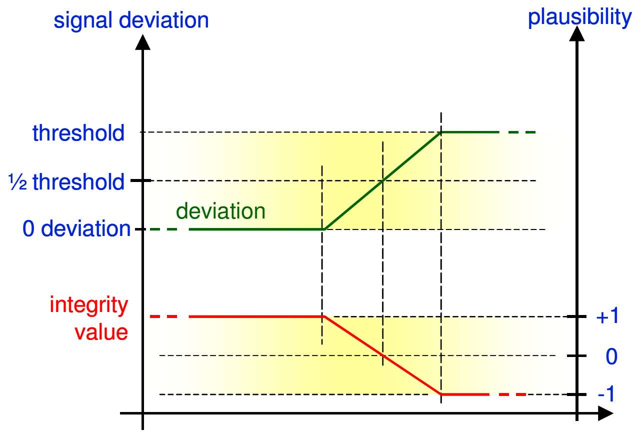

Fig 4: Redundancy based integrity value calculation

In the top sub-diagram of Fig. 5, two yaw rate signals are shown, one of which is corrupted by a continuous signal drift. The second sub-diagram shows the that the single signal monitoring is not able to detect any fault, since no singal property is exceeded. The third sub-diagram shows the result of redundancy based checking: The plausibility values of both signals are reduced equally, because the algorithm can not evaluate which signal is corrupted.

This fact underlines one inherent disadvantage of redundancy based plausibility checking: although one sensor is still intact and therefore the correct signal is theoretically available to the controller, a degradation ob both conflicting signals takes place. This leads to the need for further checking procedures: One possibility is the installation of three redundant sensors, but in most cases this exceeds the budget restrictions of production vehicles and is therefore restricted to prototype applications. A more suitable solution for series production is the implementation of model based plausibility checking algorithms, providing additional analytical redundancies for plausibility checking.

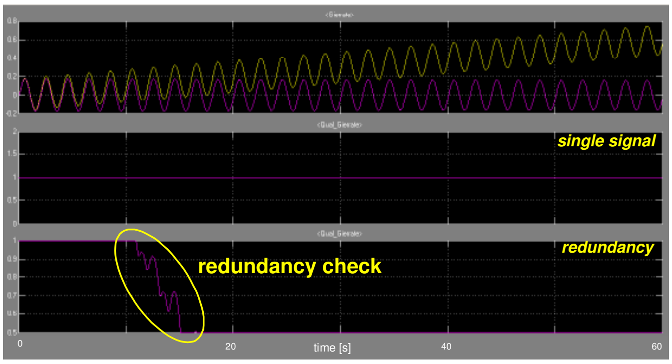

Fig. 5: Signal degradation by redundancy checking

2.3. Model Based Plausibility Checking

The model based signal plausibility checking considers the inter-relations between different signal inputs for generating plausibility judgements. Analytical redundancies are established through mathematical description and modelling of the vehicle behaviour, thus providing a basis for monitoring signal plausibility.

Depending on the signals to be observed and safety requirements, the type of models used ranges from descriptions of simple mechanical coherences to complex dynamic vehicle models. In the case of wheel speed signals, the relation between engine speed, gearbox ratio, differential gear ratio, and the speed of the driven wheels can be seen as an adequate and simple model. For verifying signals such al lateral acceleration, yaw rate or steering wheel angle, more complex dynamic models need to be used. Determined by the accuracy and dynamic range necessary, simple bicycle models or complex four wheel models are used. A very important feature for the differentiation of the models is their scope of validity. Some models, like the drive train model mentioned above, can always be assumed to be valid, while others, like a stationary bicycle model of the vehicle, may have a very restricted range of validity: dynamic driving situations, changes in vehicle parameters (mass, moment of inertia, etc.) or environmental parameters (friction) may severely influence the model accuracy.

The integrity value for the signals involved is deduced from the deviation between the calculated signal values and the measured sensor values in a process similar to the redundancy observation (see Fig. 4). Like the redundancy based plausibility checking, the model based observation is able to both reduce and increase the plausibility value. If both signal values disagree, the integrity is degraded; in case of very good correlation between measured and model generated signals, the integrity value is increased.

Fig. 6 shows the detection of a signal fault with the model based plausibility check using a stationary single track (bicycle) model. The signal defect to be found is the same as in the previous example: the sensor signal is corrupted by a continuous drift.

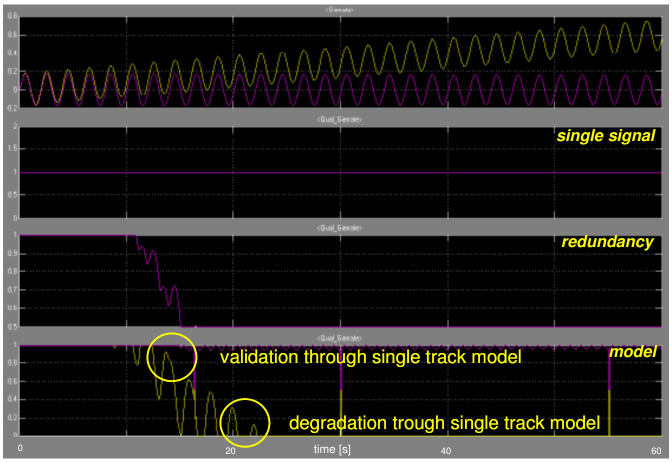

Fig. 6: Model based fault detection

Inb the example it becomes obvious, that the single signal monitoring module is not able to detect the fault (second sub-diagram). The redundancy based plausibility check detects the fault but is not able to differentiate which of the two signals is corrupted (third sub-diagram). In the last sub-diagram, the effect of the model based plausibility check is illustrated. With the increasing deviation between measured and calculated signal, the yellow signal (corrupted sensor signal) is degraded. In contrast to this, the high correlation between the second sensor signal and the model calculated value leads to a validation of the signal and thus an increased integrity value.

2.4. Methods of Model Based Plausibility Checking

The previous paragraph describes the mode of operation of the model based plausibility checking, while this section is focused on the scope of methods which are used for the model based plausibility checking.

The first necessary step is to use analytical coherences which describe fixed mechanical relations. A typical example is the relation between the gear box output speed and the wheel speeds shown in Eq. 1, another example is the connection between steering wheel angle, motor superposition angle and wheel steering angle in an active superposition steering system (Eq. 2).

$$\frac{\sum u_{wheel,j}}{j} = u_{engine} * i_{engine} * i_{differential} \qquad \text{(Eq. 1)}$$

$$\delta_{wheel} = \frac{1}{i_{Rack}} \cdot \left(\frac{\delta_{Driver}}{i_{Gear,D}} + \frac{\delta_{Motor}}{i_{Gear,M}} \right) \qquad \text{(Eq. 2)}$$

The main advantage of this kind of modelling is that the underlying models are not constrained in their validity range. Unfortunately, for most sensor signals such simple models do not apply, especially concerning the input signals for vehicle dynamics control systems. Therefore, more complex dynamic models describing the vehicle movement need to be used although either their validity range is restricted or they require greater efforts in modelling and higher calculation capacities.

More coherences between the vehicle's sensors are deduced from vehicle models. The description of the kinematic relations in a single track vehicle model delivers the inter-relation between vehicle velocity, wheel steering angle, yaw rate and lateral acceleration. The range of validity for linear bicycle models is limited to situations where the linearity assumptions apply, meaning low levels of lateral acceleration and stationary driving situations.

In order to extend the validity range to transient driving situations, dynamic modelling of the vehicle becomes necessary. In order to calculate the dynamic behaviour correctly, parameters like vehicle mass and moment of inertia need to be available and vehicle models need to be fitted to the actual vehicle behaviour. An additional possibility to further increase model accuracy is the use of four-wheel models including roll and pitch movements as well as nonlinear tire characteristics. With every step of increasing model accuracy, the validity is extended to a wider range of driving situations.

A clear drawback of complex models is the limitation of validity to the exact vehicle modelled. While a bicycle model may be valid only in linear handling situations, it applies to a wide range of vehicles with one set of parameters. A four-wheel model with nonlinear tire characteristics may be valid for nearly all driving situations but exhibits great sensitivity to changed parameters such as vehicle mass or tire properties. Other difficulties in more accurate vehicle modelling comprise parameter determination, model fitting efforts and increased calculation time. Therefore an adequate compromise between the realized performance of the plausibility checking and the effort for tuning the models has to be found.

Another option for model based plausibility checking lies in the use of adaptive vehicle dynamics observers, which generally are based on Kalman filter equations. Altough more complex in terms of implementation and calculation, such model based observers provide more robustness against parameter variations and can be applied to a wider range of vehicles.

3. PERFORMANCE DEMANDS FOR PLAUSIBILITY CHECKING

Defining error thresholds for sensor signal in systems with non-continuous intervention, like ESP systems, is a well known task. Generally, input signal errors need to be detected before the signals exceed the threshold values for system intervention. The specification of thresholds is clearly based on measurable technical relations.

A different procedure is required for systems with continuous intervention, such as active steering systems. Especially for steering systems, drivers exhibit high sensitivity for changes in the system behaviour. Therefore, the driver's subjective rating of the effects of faults is the main measure to set-up error thresholds. This directly leads to the demands on the performance of plausibility checking systems.

To set up a method for defining these demands, an examination of possible fault locations is needed first. As Fig. 7 points out, there are three main locations th be found. These are the sensors at the input side of the system, the controller of the system and the actuators at the output side of the system. The effects of faults occurring in the different locations are superimpose in the system behaviour in the order mentioned above. In an active steering system, this means that each possible fault impacts the resulting positioning error of the steering motor. Therefore, this positioning error is used for the assessment of the system performance.

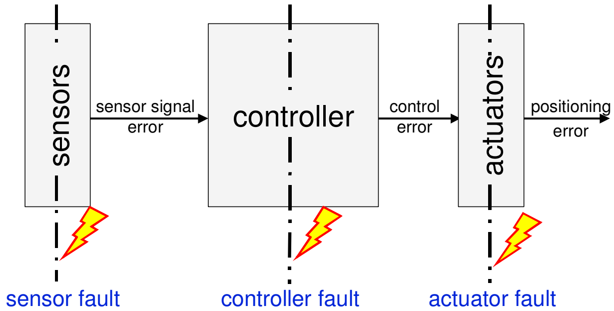

Fig. 7: Possible fault locations

According to this, a maximum positioning error needs to be defined first. This is done by rating the effects of synthetic positioning errors in driving tests with an adequate number of test persons, while driving manoeuvres adapted to the capabilities of average drivers. The importance of the subjective rating is underlined by the fact that in many cases a critical situation is not caused by the primary action (vehicle reaction to the system failure) but the secondary action (driver's reaction on unexpected vehicle behaviour).

Once the maximum positioning error is defined, the maximum control error can be deduced. This control error can then be used as a benchmark of the plausibility checking performance. To assess the fault detection performance, synthetically generated errors are inflicted upon the sensor signals, in both simulation anddriving tests. These sensor errors lead to control errors depending on the fault sensitivity of the control algorithm. The plausibility checking system needs to detect these signal errors fast enough, so that the resulting control error dos not exceed the predefined setting error.

With this procedure it is not only possible to define the maximum allowable sensor errors and with this the demand on the plausibility checking system. It also facilitates the comparison of different control concepts in terms of fault sensitivity.

4. CONCLUSION

In this contribution, an overview of a modular plausibility checking system designed for vehicle dynamics control applications is presented. The system is based on the calculation of integrity values for each signal observed. Different observation modules are used parallelly to monitor the compliance of each signal's propertie with its specifications (single signal monitoring) signal, to evaluate the integrity of signals from redundant sensors (redundancy based plausibility check) and to compare sensor input signals to model generated signals (model based plausibility check). The functionality of the different fault detection modules and their limitations are shown using different examples.

The models used in model based are analysed regarding their validity for different driving situations and vehicles; the advantages and disadvantages of complex vehicle modelling for plausibility checking are discussed.

A procedure is described for obtaining performance requirements for plausibility check based on vehicle and driver reactions. This procedure is explained using the example of an actively steered vehicle.

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