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Sensor system optimization to meet reliability targets

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ABSTRACT

In this work, we show the influence of sensor system measurement uncertainties to sensor system reliability and ways to meet reliability targets. A general model to handle measurement uncertainties is defined and the according influence to reliability is presented, which is defined as probability of meeting specification requirements. Initial step is to optimize sensor systems concerning lowest influences of sensor system parameter fluctuations to the measurement uncertainty using statistical optimization methodologies. In case the influence of unknown nuisance parameters cannot be sufficiently suppressed, such parameters may be additionally measured in order to further reduce measurement uncertainties. The remaining uncertainties are again addressed using statistical optimization methodologies. Finally, measurement uncertainty also affects the reliability of such a system. For sensor systems in safety critical applications it may thus be required to include measures such as redundancy. This is also included in the investigations. Further examples for explained optimization methodologies of measurement uncertainty reduction are presented.

1. Introduction

Our modern world is fully digitized: starting from consumer goods such as mobile phones, TVs and body scales, going to vehicles such as cars, airplanes and trains to automated production lines based on human-robot-interaction. All of these electronic devices need a way to interface to the real, physical world: commonly, sensor systems present a way to realize this interfacing. These sensor systems present the means for electronic systems to comprehend their environment. Depending on the application, it is more or less important that this comprehension is truthful and dependable. As soon as a physical quantity of interest and its representation (analog or digital) from sensor systems differ too much in value, this is either useless – in case of the smart watch which does not reliably sense our heart frequency – or dangerous in case of the accelerometer which is in charge of the airbag control. Sensor system reliability is thus a major concern, not only in terms of customer satisfaction, but also for safety reasons. In this work, we consequently present means to define and quantize reliability by introducing a general mathematical model. Ways to improve the sensor systems' reliability are presented: one way is to use optimization methods of the existing systems using statistic optimization techniques [1], another way is to additionally measure known, correlated disturbing influences and compensate those [2, 3], and also a combination of both approaches is possible. Where the effort is justified by the application, redundancy can be a way to improve the sensor system reliability, especially for safety requirements. The latter is often the case in standardized safety related automotive applications [4].

1.1. Sensor system definition

A general abstraction of a sensor system is illustrated in Fig. 1. Here θ is the physical quantity of interest. Depending on the employed sensor effect, this is further converted into the electrical domain by the sensor front-end or subsequent circuitry. It is now an (analog or digital) electrical quantity and represented by the Random Variable (RV) Y. A RV basically is a function which, besides possible deterministic variables, also depends on random, i.e. unknown, inputs. In system theory, such functions, which describe the way of how a system acts on a quantity of interest, are often also called transfer-functions. Here, it is assumed that Y depends on systematic influences (bias-voltage, calibration-parameters, stress etc.) [2, 3] as well as random influences (noise, Electro Magnetic Interference (EMI) etc.) introduced by the sensor front-end and/or respective circuitry. To reconstruct the physical quantity from the electrical representation Y, a mapping function as part of the digital signal processing is necessary. This mapping function is termed an *estimator* for the physical quantity of interest and its sensor system output value is often denoted as $\hat{\theta}$ to indicate the relation to the true physical quantity of interest (θ). This estimation even can be performed inside the sensor system with electrical output values interpreted in the same physical quantity as θ [1].

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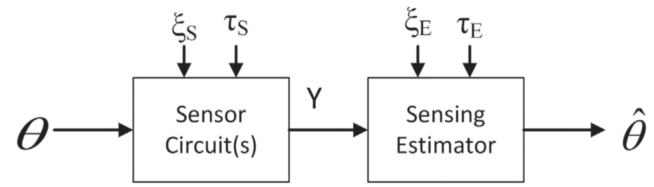

Fig. 1. General block diagram of a sensor system with transfer of a physical quantity θ into electrical signals Y with estimation to an interpretable output value M to get an interpreted estimation of the real value $\hat{\theta}$.

1.2. Sensor system deviations

The way to express measurement uncertainty and methods to mathematically deal with them are defined in the *Guide to the expression of uncertainty* [5] and respective supplements. For existing sensor systems, the tolerable uncertainties and deviations are limited by specifications. When a new sensor system is implemented, these specifications are the design criteria for sensor system optimization. As explained before and compare Eq. (1) the sensor circuit output value Y (or output vector Y) depends on systematic parameters, now termed ξ, and random terms, which we now call τ. In terms of transfer-functions, we can split it into the ideal transfer-function $h(\cdot)$ and the deviation transfer-function $e(\cdot)$. From measurements, Y an estimation of θ called $\hat{\theta}$ can be found via $u(\cdot)$ by Eq. (2). The final deviation in Eq. (3) is the difference between sensor output and ideal value.

$$Y = h(\theta, \xi) + e(\theta, \xi, \tau) \tag{1}$$

$$\hat{\theta} = u(Y, \xi, \tau) \tag{2}$$

$$\Delta = \hat{\theta} - \theta \tag{3}$$

Some of the most common sources of measurement uncertainties and deviations are:

- Noise (thermal, quantization)
- Production (spread)
- Influencing parameters (temperature, stress)
- Calibration (calibration deviation/quantization)
- Lifetime drifts (aging)
- External sources of deviation (Strayfields, EMI)
- Sensor system faults

1.3. Definition of reliability and unreliability

The reliability of a sensor system acc. [6] is defined as the *ability of a product to perform a required function at or below a stated failure rate for a given period of time*. We further define the *required function* as correctly providing measurement results within the specification limits at specified conditions (e.g.: temperature, supply-voltage, lifetime). In engineering, a more often used term is unreliability which is the probability of a sensor system providing measurement value outside the specification (failures). Several standards are available dealing with reliability or unreliability (eg.: Ref. [7]) or at least to verify them in automotive [8], industrial [9] and general dependability standards [10]. In this work, we consider measurement uncertainty as Gaussian distributed deviations of the sensor output value $\hat{\theta}$ from the ideal output value θ according Eq. (3). Since we assume Gaussian distributions of measurement deviations with average deviation μ and variance σ^2 according to the general definition of the respective probability density function (pdf) shown in Eq. (4) there is always a probability larger than zero to violate specification limits, mathematically because of the infinite spread Gaussian distribution. In this work we assume hardware-faults as Gaussian distribution with larger and unknown variance. As the variance of deviations caused by faults is unknown, we consider the worst case. In practical setting, a maximum

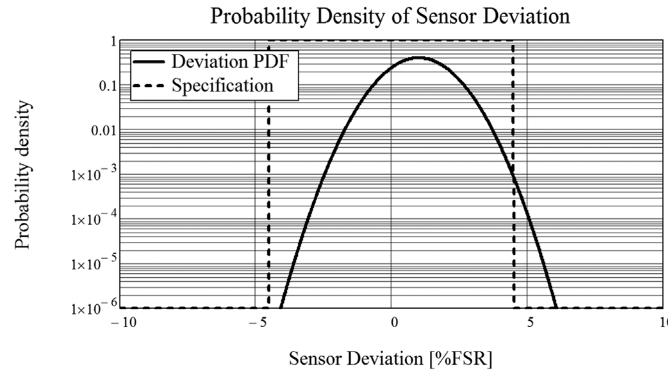

Fig. 2. Gaussian distribution of all present measurement uncertainties shown together with specification limits in logarithmic scale.

number of specification limit violations are allowed and measured as probability in % or parts per million (ppm). An example with sensor deviations in % of measurement full-scale-range (%FSR) acc. [11] comprising statistical and systematic deviations is shown in Fig. 2.

$$pdf(\Delta) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left(\frac{(\Delta-\mu}{\sigma}\right)^2}. \tag{4}$$

Unreliability in this sense is the integral of all probability densities outside the minimum and maximum specification limits $\pm\,\Delta_{spec}$. Mathematically it can be written as shown in Eq. (5). This unreliability or probability of specification violation is dependent on mean-value and variance of this modeled Gaussian distribution. These probabilities can be determined relative to the specification limit according Fig. 3.

$$P_{fail}(|\Delta| > \Delta_{spec}) = \int_{-\infty}^{-\Delta_{spec}} pdf(\Delta) + \int_{+\Delta_{spec}}^{+\infty} pdf(\Delta). \tag{5}$$

2. Sensor system optimization methods

We want to optimize the sensor output concerning reliability to provide sensor output values within specification limits. In general, this optimization criterion can be defined by $\psi(\cdot)$, which depends on the input variable θ and the design parameters ξ. Since θ is given, only the

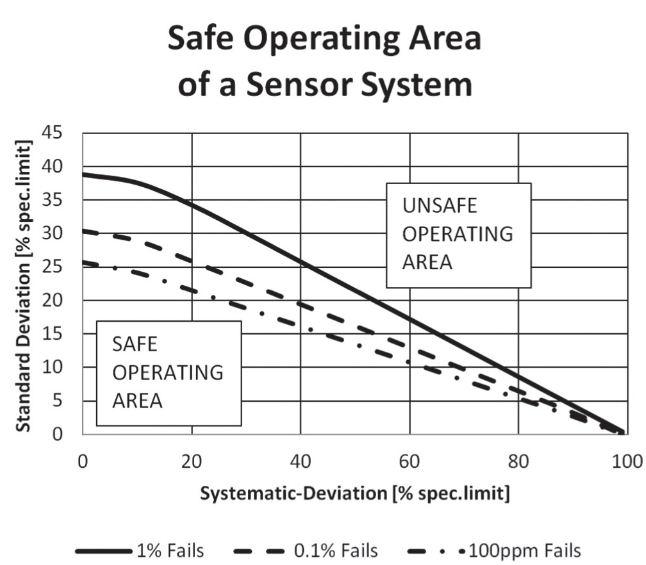

Fig. 3. This graph shows the safe/unsafe operating area (SOA) of a sensor system providing data within specification limits and assuming Gaussian distribution of deviations with parameters mean and standard-deviation. These parameters are scaled in % relative to the specification limit and thus are valid for all possible limits.