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Efficient cross-sensitivity compensation in multisensor systems by half-blind calibration

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ABSTRACT

Sensor systems designed to determine external measurands often show parasitic sensitivities to other influences, so-called disturbances. Calibration of such a system aims for the extraction of disturbance-compensated measurand values from the system output signals. Often this goal is achieved by exposing the system to a sufficient number of load conditions involving well-controlled values not only of the measurands but also of the disturbances. In this work we show that the calibration effort focused exclusively on the extraction of disturbance-compensated measurand values can be considerably reduced in the case of systems with linear response. The conclusions therefore apply to Hall, piezoresistive stress, and temperature sensors, among others. During the calibration procedure, well-controlled measurand values need indeed to be applied to the system; however, while all disturbance parameters need to be varied during calibration, accurate knowledge of their values is not needed. By making use exclusively of the calibration measurand values and the concurrently extracted sensor signals, it is possible to determine a reduced calibration matrix which ensure the successful extraction of disturbance-compensated measurand values from sensor signals. The effectiveness of the method is demonstrated using a six-degree-of freedom linear force-moment microtransducer with redundant sensors. The method may save cost by simpler calibration setups and the time-saving procedure it proposes.

1. Introduction

Instead of responding only to the influences they were designed to measure, many sensors and sensor systems are cross-sensitive to external parameters whose measurement is not of primary interest [1,2]. For example, many sensors are cross-sensitive to temperature. Chemical sensors are notorious for their limited specificity, which is another way of stating their cross-sensitivity to interfering chemical species [3]. Parasitic sensitivities also affect Hall sensors, which respond not only to the magnetic field of primary interest but also to mechanical stress [4–7] and temperature gradients [4]. Resonant time standards are known to show unwanted mechanical and thermal cross-sensitivities [8,9]. Likewise, the compensation of undesired cross-sensitivities has been a constant challenge in inertial sensors with multiple degrees of freedom [10,11].

Cross-sensitivities call for effective compensation methods [1,12]. One option is the differential approach. It relies on a pair of sensors, only one of which is exposed to the measurand of interest, while both experience identical exposure to the remaining conditions. In perfectly matched pairs, the output signal difference of the two devices reflects only the wanted measurand. This principle has been successfully implemented with infrared radiation sensors [13], thermal converters [14], thermal pressure sensors [15], and chemical sensors [16], to name a few examples. A voltage-biased resistive half-bridge is a measurement structure where parasitic influences, such as temperature, acting similarly on the two component resistors are inherently suppressed [17].

The technological approach to cross-sensitivity compensation strives to implement material combinations that minimize parasitic sensitivities. In the case of micromechanical resonators useful for timing devices, for example, a thin silicon oxide layer covering the silicon resonators has allowed to improve the long-term stability to 2 ppm [18].

The physics-based approach exploits fundamental properties of sensors whose response to various influences depends on the operating conditions of the sensor. Such dependences can be exploited to eliminate undesired signal components. An example is the semiconductor Hall sensor whose Hall voltage remains

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constant under current rotation in the so-called spinning current method [19], while the pseudo-Hall voltage caused by mechanical stress, alternates in sign from mode to mode [20,21]. By averaging over successive modes, one thus eliminates the mechanical cross-sensitivity [4,6]. Similarly, the thermal cross-sensitivity of vertical semiconductor stress sensors was successfully suppressed by modulating the width of the pn-junctions delimiting the current flow in the sensor [22].

This paper builds on the multisensing approach. This means the compact combination of several sensors into a system. Some of the sensors may be included with the sole purpose of providing specific compensation signals [12]. Even in sensors designed, optimized, or operated according to the above-mentioned approaches, residual cross-sensitivities may still call for the integration of compensation sensors. For example, temperature sensors co-integrated with mechanical sensors serve the purpose of thermal cross-sensitivity compensation [23]. Stress sensors surrounding Hall sensors achieve the same effect regarding the mechanical influences to which a magnetic sensor may be exposed in its package [24]. Mechanical multisensor systems designed for measuring components of forces and moments applied to the system have relied on combinations of optimally placed stress sensing elements responding with different sensitivities to the individual load components. This allows force and moment components to be deduced from the ensemble of sensor signals [25–29]. Viewed from the point of view of each individual force or moment component to be measured, the procedure is equivalent to a successful compensation of the influence due to the others.

In the following, we denote the measurands of primary interest in the context of a sensor system by $\boldsymbol{m}$. Influences whose measurement is not the goal of the sensor system, but that nevertheless act on it, can be considered as disturbances and shall therefore be captured by the symbol $\boldsymbol{d}$. Bold-font lower-case and capital letters in this paper denote vectors and matrices, respectively. In the case of $\boldsymbol{m}$ and $\boldsymbol{d}$, this takes into account the fact that both may have more than one component.

The calibration challenge in the context of multisensor systems has been addressed in the past by work on the shape-from-motion approach [30] and the device hyperplane characterization (DHPC) method [25], and with special focus on the question of how to optimize the sensor arrangements in redundant sensor systems [26]. The goal of an effective calibration procedure is to ensure that the sensor system enables $\boldsymbol{m}$ to be determined free of the influence of $\boldsymbol{d}$. Note that this does not imply that $\boldsymbol{d}$ has to be determinable by the system as well. For this reason we were led to hypothesize that the reduced goal of exclusively extracting disturbance-free measurands $\boldsymbol{m}$ can be reached with a correspondingly reduced calibration effort.

Building on previous work in this area [25,30], we show how to design such a reduced calibration strategy. We term it half-blind calibration (HBC). The reduced effort regards the application of disturbances during calibration. Since calibration load measurements constitute a potentially delicate and often time and resource consuming aspect, an efficiency gain can be expected.

In this paper we limit ourselves to the case of sensor systems responding linearly to $\boldsymbol{m}$ and $\boldsymbol{d}$. The analysis relies on the method of multivariate linear regression using least squares. Likely, HBC can benefit from other, advanced multivariate regression techniques such as principal component regression (PCR) [31], ridge regression (RR) [32], and partial least squares (PLS) regression [31]. This will be considered in Section 5.

After making the necessary definitions in Section 2, the HBC method is introduced in Section 3. Thereafter, Section 4 illustrates the theoretical considerations with data from a redundant mechanical sensor system of our design. Section 5 closes the paper with a discussion and conclusions.

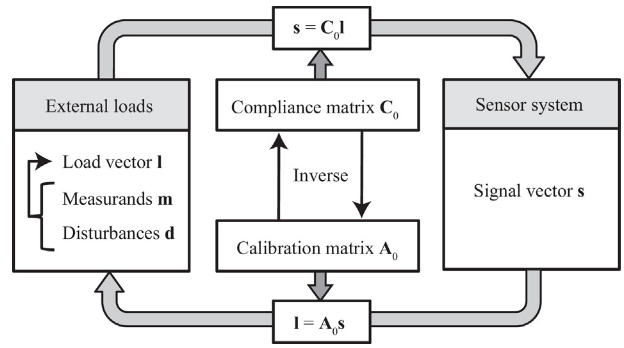

Fig. 1. In minimal sensor systems with $n_s = n_l$, any load $\boldsymbol{l}$ results in a sensor signal vector $\boldsymbol{s}$ via the compliance or sensitivity matrix $\boldsymbol{C}_0$. Vice versa, from any measured sensor signal vector $\boldsymbol{s}$ one is able to infer the load vector $\boldsymbol{l}$ that caused it via the calibration matrix $\boldsymbol{A}_0$.

2. Basics of linear sensor system calibration

The linear relationship between the n_s sensor signals constituting the vector $\boldsymbol{s}$ and the n_l load components constituting the vector $\boldsymbol{l}$ is conventionally described by the compliance matrix $\boldsymbol{C}_0$ via [26]

$$\boldsymbol{s} = \boldsymbol{C}_0\boldsymbol{l}. \tag{1}$$

In the sensor literature, $\boldsymbol{C}_0$ is also termed sensitivity or transfer matrix. The vector $\boldsymbol{l}$ is assumed to be composed of n_m measurands $m_1, \ldots, m_{n_m}$ constituting $\boldsymbol{m}$ and n_d disturbances $d_1, \ldots, d_{n_d}$ constituting $\boldsymbol{d}$. Both $\boldsymbol{l}$ and $\boldsymbol{s}$ are assumed to be offset-compensated. Please note that the term “load” in this paper is not restricted to the idea of mechanical load. It can designate any mechanical, thermal, electrical, magnetic, radiant, or chemical influence resulting in a system response.

Successful sensor calibration ensures that a load state $\boldsymbol{l}_e$ can be reliably extracted from its sensor signal state $\boldsymbol{s}_e$ via

$$\boldsymbol{l}_e = \boldsymbol{A}_0\boldsymbol{s}_e, \tag{2}$$

where $\boldsymbol{A}_0$ denotes the calibration matrix, also termed stiffness or exploitation matrix [30,33,34]. In a noise-free and well-designed sensor system with identical numbers of sensors and load components ($n_s = n_l$) the inversion of (1) into (2) is a well-posed problem with $\boldsymbol{A}_0 = \boldsymbol{C}_0^{-1}$, with the superscript −1 denoting matrix inversion. This ideal situation is illustrated in Fig. 1.

In redundant sensor systems with $n_s > n_l$, $\boldsymbol{C}_0$ is rectangular and has no inverse in the conventional sense. However its Moore-Penrose pseudoinverse $\boldsymbol{C}_0^+$ can be computed [35]. Furthermore, if $\boldsymbol{s}_e$ is affected by noise, it will not be possible to solve $\boldsymbol{s}_e = \boldsymbol{C}_0\boldsymbol{l}$ for the unknown $\boldsymbol{l}$ since $\boldsymbol{s}_e$ in general lies outside the range of $\boldsymbol{C}_0$ [35]. Nevertheless, given such a general $\boldsymbol{s}_e$, the best approximate solution of (1) in the sense of multivariate linear regression is found to be $\boldsymbol{l}_e = \boldsymbol{A}_0\boldsymbol{s}_e$ with the calibration matrix $\boldsymbol{A}_0 = \boldsymbol{C}_0^+$ provided $\boldsymbol{C}_0$ has rank n_l [35].

The purpose of calibration is to experimentally determine $\boldsymbol{A}_0$. As schematically shown in Fig. 2, a calibration setup allows the sensor system to be exposed to all relevant load components, while the system is tightly coupled to a set of reference sensors able to independently measure the applied loads. The calibration matrix is then determined by applying n_c calibration load cases $\boldsymbol{l}_i^{(c)}$, with $i = 1, \ldots, n_c$, and by reading out the corresponding sensor signal vectors $\boldsymbol{s}_i^{(c)}$ [25]. The calibration load vectors are arranged column by column into the so-called calibration load matrix $\boldsymbol{L}_c = (\boldsymbol{l}_1^{(c)}|\ldots|\boldsymbol{l}_{n_c}^{(c)})$. For