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Minimal Model Selection for Calibrating a Hall-Stress-Temperature Multisensor System Using LASSO Regression

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Summary:

The proposed method takes advantage of LASSO regression to select a reduced-complexity polynomial model for calibrating nonlinear multisensor systems, while addressing the trade-off between higher accuracy and smaller calibration effort. The method is applied to compensate the nonlinear thermal and mechanical cross-sensitivities in a Hall-stress-temperature multisensor system. It enables to (i) reduce the calibration effort, measured by the number of model parameters, by a factor of 1.5 within the space of 4th-order polynomial models without compromising accuracy or to (ii) improve the accuracy by strategically including higher-order polynomial terms without increasing the number of model parameters.

Keywords: Calibration, multisensor system, regularization, LASSO, model selection.

Background

The model selection for nonlinear multisensor systems (MSS) is a crucial task, since the calibration and computational effort grows rapidly with increasing model complexity, e.g. polynomial order *P* and number of sensors in the system [1]. Regularization methods such as the least absolute shrinkage and selection operator (LASSO) regression have been applied to reduce model complexity of biomarker data [2] and chemical nanosensors [3]. This study demonstrates how to successfully combine LASSO regression and ordinary least square regression (OLSR) in the context of nonlinear MSS calibration.

Description of the New Method

When the LASSO regularization parameter λ is varied from 0 to 1, the number of calibration parameters in the multiple polynomial regression of MSS calibration data is progressively reduced from the full number to zero [4]. At the same time, the achievable accuracy progressively worsens, since contributing parameters are suppressed. However due to statistical variability in sensor data, for a given reduced number of parameters, LASSO may provide several competing reduced models. Evaluating all of them on the calibration data from an ensemble of MSS using OLSR allows then to identify the one best suited for modelling the general response of the MSS. Thereby, the method allows to strategically address the trade-off between model complexity of nonlinear MSS and the achieved accuracy.

Results

Figure 1 illustrates the procedure for selecting the optimal reduced polynomial compensation function f_{comp} allowing to make the sensitivity S_H of a Hall sensor system independent of temperature *T* and stress σ.

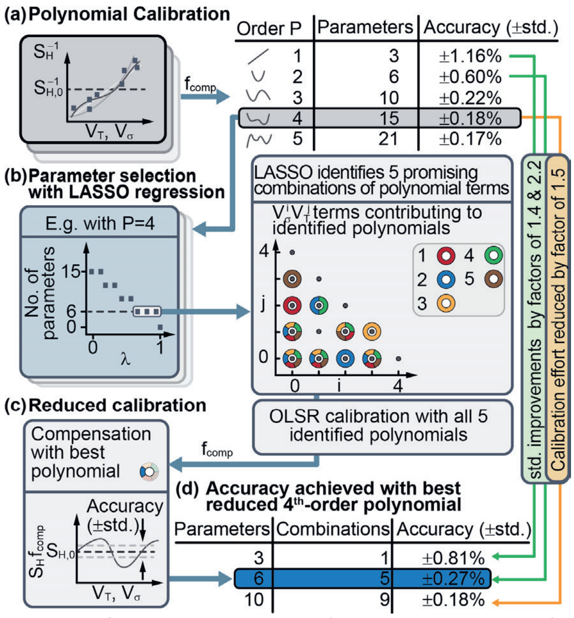

Fig. 1. Schematic diagram of the applied method for selecting minimal nos. of calibration parameters. (a) Conventional polynomial OLSR calibration of inverse Hall sensitivity up to polynomial orders 5 and achieved accuracies. (b) Polynomial term selection using LASSO illustrated for P = 4; identification of 5 reduced polynomial candidates, each with 6 terms. (c) OLSR calibration with 6 remaining parameters and (d) sensor accuracy achieved with best LASSO-reduced 4th-order-models with 3, 6, and 10 remaining parameters.

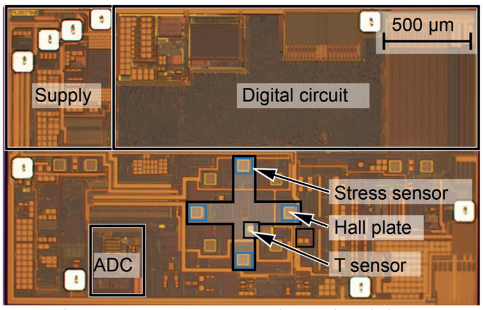

Figure 2: Optical micrograph of the CMOS Hall-stress-temperature sensor system designed to measure magnetic field B values compensated for temperature T and stress σ.

For each of 12 samples of MSS (Fig. 2), 88 calibration load cases and 44 test load cases are used to validate the procedure. An automated measurement setup (Fig. 3) enables the application of a magnetic induction of ±25 mT, temperature variations in the range of –40 °C to 125 °C, and forces up to 15 N resulting in compressive isotropic mechanical in-plane stress down to about –100 MPa. The calibration data of the samples are shown in Fig. 4. The inverse relative Hall sensitivity S_H^{-1} is taken as the regressand, whereas the T sensor signals V_T and σ sensor signals V_σ serve as regressors. The outcome is $f_{comp}(T, \sigma)$, which turns the cross-sensitive S_H into the T and σ compensated, constant $S_{H,0} = S_H f_{comp}$. As an example, starting with a 4th-order polynomial regression with 15 parameters, depending on the MSS sample LASSO produces 5 different polynomial models with only 6 remaining parameters (see Figs. 1(b) and 5). For each of these models, an OLSR calibration is performed on the calibration data of all MSS and the best model is identified (see Fig. 1(c), blue polynomial); it results in a compensated sensitivity

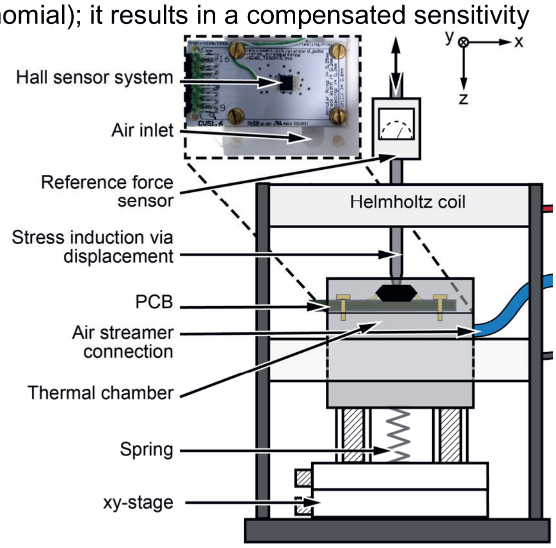

Figure 3: Schematic and photograph of automated measurement setup for calibrating Hall-stress-temperature sensor systems. Induction B, temperature T, and stress σ are applied via Helmholtz coil, air stream into thermal chamber, and mechanical loading mechanism, respectively.

with an uncertainty of ±0.27% (see Fig. 6). This is twice as good as the accuracy achieved with a 2nd-order polynomial with 6 parameters as well, but resulting in an uncertainty of ±0.60%. Likewise (see Figs. 1(a, d)), the LASSO reduction to 3 and 10 parameters, implying the same calibration effort as full 1st and 3rd-order models, lead to significant accuracy gains from 1.16% to 0.81% and from 0.22% to 0.18%, respectively.

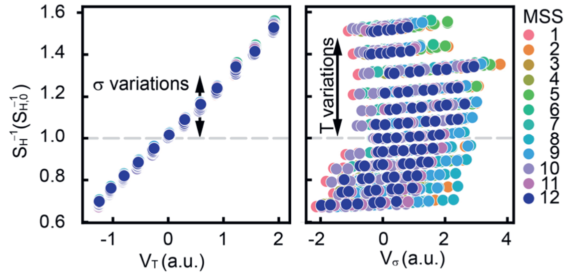

Figure 4: Measured calibration data: T and σ dependent, uncompensated inverse Hall sensitivity of 12 MSS vs. respective output signals V_T (left) and V_σ (right) of T and σ sensors.

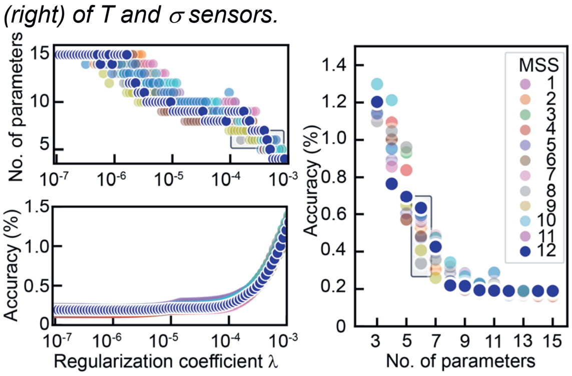

Figure 5: LASSO selection of reduced polynomials (with reduced nos. of model parameters) depending on the wanted accuracy (left). Several polynomials are identified from the individual MSS (right); the best one is chosen by applying OLSR to all MSS.

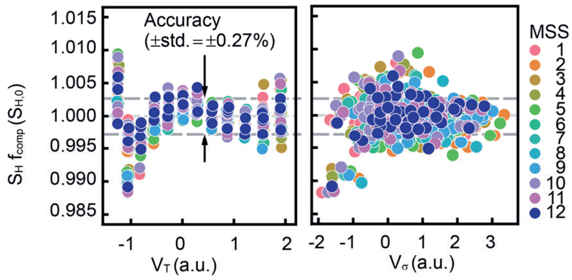

Figure 6: Hall sensitivities of 12 MSS compensated with the best 4th-order polynomial f_{comp} with only 6 parameters.

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