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A Framework for Calibration of Barometric MEMS Pressure Sensors

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Abstract

Barometric MEMS pressure sensors must be calibrated at several temperatures and pressures. The fewer calibration points are needed to fulfill a sensor specification, the faster sensor production is. This paper proposes a polynomial approach for determining optimal sensor calibration, using the minimum number of calibration points necessary. In an experiment the framework is applied to the following sensor types: Bosch BMP085, Bosch BMP180, and EPCOS T5400. Influences of temperature operation range and pressure range are discussed in the experiment. Further, optimal calibration point suggestions are identified.

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Keywords: Barometric MEMS pressure sensors, calibration framework, calibration point selection, polynomial calibration, least square

1. Introduction

Barometric MEMS pressure sensors are used in mobile devices to determine relative height changes [1] and absolute barometric air pressure. As the last step of production, they are calibrated under various temperature and barometric pressure conditions [2]. Reading the sensors response at different temperatures and pressures significantly increases the sensor production time and cost. To keep calibration time as short as possible, this paper proposes an algebraic framework for barometric MEMS pressure sensor calibration. The framework is capable of determining optimal calibration point combinations for a given product specification (temperature working range

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and pressure working range). The paper is structured as follows: Sec. 2 is an introduction to the proposed framework and describes the methods used within. Sec. 3 shows an experiment with three different kind of commercial barometric MEMS pressure sensors, to illustrate the frameworks capabilities. Sec. 4 contains the conclusions.

2. Framework for Calibration

A framework for sensor calibration analysis is implemented in the programming language Python. The proposed framework uses a polynomial approach for sensor calibration. As shown in Tab. 1., the framework processes measurement data (raw MEMS sensor temperature, raw MEMS sensor barometric pressure, reference barometric pressure, reference temperature) in sensor objects. Having more than one sensor in a batch, a calibration module is implemented as container for handling multiple sensor objects and for calculation of all possible calibration point combinations.

Sensor Object	Optimization Module	Calibration Module	Statistics Module
1 Container for measurement data (raw temperature, raw pressure, temperature reference, pressure reference)	1 Polynomial order selection	1 Sensor batch handling	l Tools for statistical evaluation of result files (selection, combination, sorting, filtering)
2 Methods for data import handling	2 Solver (Least Square Fit or analytical)	2 Calculation of all possible calibration options	2 Tools for result visualization (distribution plots, boxplots, histogram)
3 Methods for data segmentation	3 Parameter weighting	3 Result file management	
	4 Data point selection		

Table 1. Structure and functions of the proposed calibration framework

2.1. Calculation of calibration options

For a database of n temperature points and m pressure points for calibration, a polynomial calibration of order t in temperature and order p in pressure provides

$$c = \binom{m}{p+1}^{p} \binom{n}{t+1}^{t}$$
(1)

possible calibration point combinations. For all following considerations, we assume a dataset of (-40 °C, -30 °C, 0, ..., 90 °C) test temperature points and (300 hPa, 400 hPa, ..., 1100 hPa) test pressure points. This dataset covers most state-of-the-art operation ranges of barometric MEMS pressure sensors. For a quadratic temperature term and linear pressure term in the calibration polynomial, the assumed dataset delivers c = 4.769.856 calibration options. An increase to quadratic order in *p*, while leaving *t* quadratic, leads to c = 934.891.776 calibration options. For each option the framework has to perform a least-square optimization loop (in the optimization module, shown in Tab. 1.) and a root-mean squared error calculation for determining the pressure error over the whole test condition dataset.

2.2. Statistical evaluation

The framework uses the root-mean-squared error (rms error) to evaluate whether a certain calibration result belongs to the group of best 1 %, or not.

Comparing all variants for calibration, the worst 99 % of calibration options are dismissed. The rest (1% of all calibration options) is used for evaluation (histograms, error landscape, frequency plots, etc.).

3. Experiments

In this section the proposed calibration framework is evaluated in two experiments for each six sensors of the types: 'EPCOS T5400', 'Bosch BMP 180' and 'Bosch BMP 085'. The measurement dataset, as explained in Sec. 2.1, was recorded for each sensor soldered on PCB. The test equipment uses a pressurized climate chamber, a *General Electric PACE 5000* pressure controller and a combination of Peltier-Elements and type K thermocouple for reference temperature control.

3.1. Sensor nonlinearity

The sensors were investigated for their linearity over the pressure range at temperatures from -40 °C to 90 °C. Raw value data obtained under all temperature and pressure test conditions were used for a least-square fit. The fit minimizes $c_1 T_{raw} + c_2 P_{raw} + c_3 = P_{ref}$, where T_{raw} is the raw sensor temperature readout, P_{raw} denotes the raw sensor pressure readout, P_{ref} is the reference sensor pressure and $c = [c_1, c_2, c_3]$ is the calibration result vector, determined by the least-square fit. In Fig. 1 the rms error of the calibrated pressure signal is plotted over temperature range for the reference pressure isobars 300 hPa, 700 hPa and 1100 hPa. All pressure sensors investigated show nonlinear behavior. Especially the Bosch sensors show several 100 hPa rms error at low temperatures. The BMP 085 sensor shows more error variance in a sensor batch at temperatures from 0 °C to 60 °C, compared to the smaller packaged BMP 180 sensor.



Fig. 1. Linear calibrated (p=1, t=1) pressure signal error at test pressures (300 hPa, 700 hPa, 1100 hPa) and defined test temperatures.

3.2. Calibration point selection

In MEMS sensor production, sensors are tested and calibrated at a defined set of pressure and temperature points. The proposed framework is used to calculate which combinations of calibration points for p = 1 and t = 2 are most likely to appear within the best 1 % of all possible calibration options. The experiment results are depicted in a distribution landscape plot in Fig. 2. In the upper part of Fig. 2 the relative frequency of temperature/pressure point combinations for the first pressure point selected is shown. For all three kinds of sensors investigated, the calibration point combination low pressure / high temperature appears most likely. For the second pressure point selected, the combination high pressure / low temperature is most likely for the Bosch BMP 180 and the Bosch BMP 085, having



another peak at low temperature and pressure around 900 hPa. For the EPCOS T5400 sensor, various temperature points over the full temperature range at high pressure are likely to appear within the best 1 % calibration options.

Fig. 2. Frequency landscape of best 1% calibration point combinations in polynomial (t=2, p=1) sensor calibration.

4. Conclusion

The proposed framework was used to find optimal calibration point combinations for a t = 2, p = 1 calibration polynomial. Points selected at the upper and lower boarders of specification have an increased likelyhood to appear within the best 1 % calibration options. In another experiment sensors are calibrated with the least square solution for a t = 1 and p = 1 polynomial. The experiment showed that all sensors tested have a clearly nonlinear behavior over the test specification (temperature, pressure). Especially at the specification borders, Bosch sensors show a clear nonlinear behavior. In general the framework developed can be used to investigate, visualize and optimize MEMS sensor calibration. For further work, calibration point extrapolation will be implemented to improve calibration results by adding offset values to the calibration polynomial and calibration uncertainty will be calculated [3,4].

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