Identification, Calibration and Control for Motor Commutation

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Identification, Calibration and Control for Motor Commutation

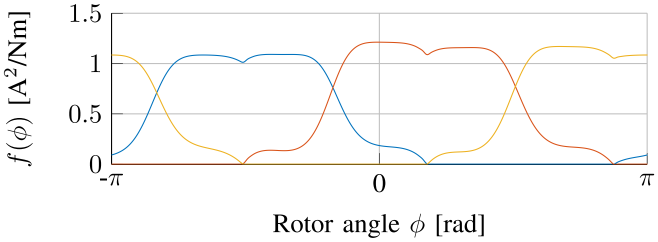
Max van Meer[1], Gert Witvoet[1,2] and Tom Oomen[1,3]

I. RESEARCH OVERVIEW

Switched Reluctance Motors (SRMs) [1] enable power-efficient actuation with mechanically simple designs. These actuators exhibit a highly nonlinear relationship between torque, coil currents, and rotor position, challenging position feedback control. In this abstract, some key challenges in the identification, control, and calibration of SRMs are addressed.

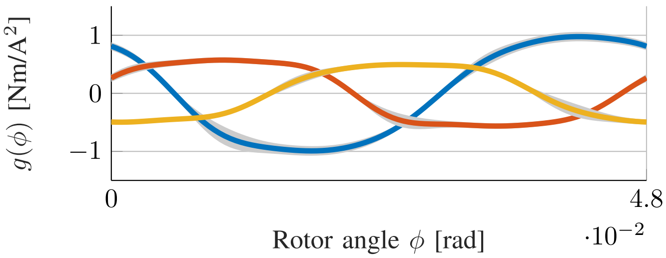
Optimal Commutation for Switched Reluctance Motors [2]

To allow for LTI feedback control of SRMs, the nonlinear dynamics are linearized by designing a commutation function that produces multiple coil currents based on desired torque and the rotor position. In [2], a novel approach to commutation function design through convex optimization is developed, yielding a high degree of control over and interpretability of the current waveforms.



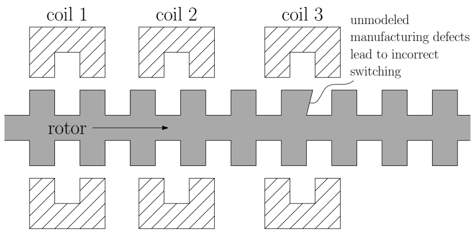
Nonlinear Bayesian Identification for Motor Commutation

The commutation function design of SRMs relies on a model of the nonlinear torque-current-angle relationship of the system in question. This relationship is identified using Bayesian estimation. Experimental results confirm that a good model is obtained, even without torque sensors or extensive knowledge of the nonlinear structure. Moreover, an expression of the model variance is obtained, quantifying the uncertainty that results from, e.g., tooth-by-tooth variations and manufacturing tolerances.



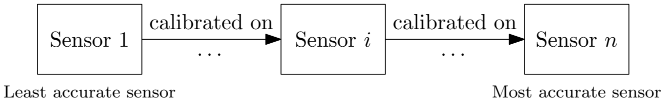
Robust Commutation Function Design

When an uncertain model of the torque-current-angle relationship of an SRM is available, this uncertainty can be explicitly taken into account in the design of commutation functions. By exploiting the optimization-based commutation design framework from [2] with a cost function that penalizes the expected value of torque ripple given the uncertain model, commutation functions are obtained that are robust to tooth-by-tooth variations and other modeling errors.



Cascaded Calibration of Mechatronic Systems via Bayesian Inference [3]

Actuators that feature a teethed rotor made from a soft magnetic material, such as SRMs, lend themselves well to Hall-effect position sensors, as these rely on the rotor teeth to yield a position measurement. However, these sensors exhibit significant position-dependent inaccuracies and hence require calibration on an external test bench. The next page summarizes a novel approach to cascaded position sensor calibration that also takes into account the calibration of the test bench to achieve more accurate calibration.



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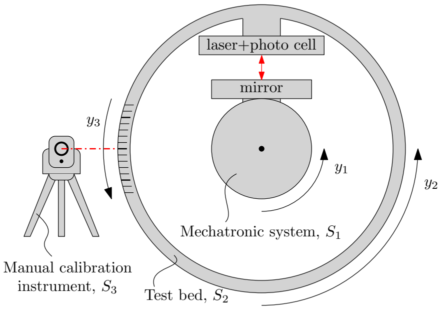
II. SEMINAR TOPIC - CASCADED CALIBRATION VIA BAYESIAN INFERENCE [3]

A. Background

The objective is to model the relationship between a low-cost, relatively inaccurate sensor ($S1$) and a highly accurate manual instrument ($S3$). To achieve this, a test bed is employed, incorporating a sensor ($S2$) that has been calibrated against $S3$. Following this initial calibration, a diverse range of products, each equipped with its own S1 sensor, undergoes automated calibration on the test bed. This process aims to ensure accurate mapping between $S1$ and the reliable reference provided by $S3$.



B. Cascaded Calibration using Bayesian Inference

The main concept revolves around modeling the intermediate sensor calibration, denoted as $f_{2\to3}$, as a Gaussian Process (GP) [4]. This model captures the mapping from the readings of sensor S_2 to those of sensor S_3 as follows:

$$y_3 = f_{2\to3}(y_2), \tag{1}$$

where y_2 and y_3 represent the measured positions by sensors S_2 and S_3 respectively. By collecting a dataset $\mathcal{D}$ from these sensors and employing GP models for $f_{2\to3}$, the posterior model variance, denoted as $\text{cov}(\hat{f}_{2\to3})$, can be calculated.

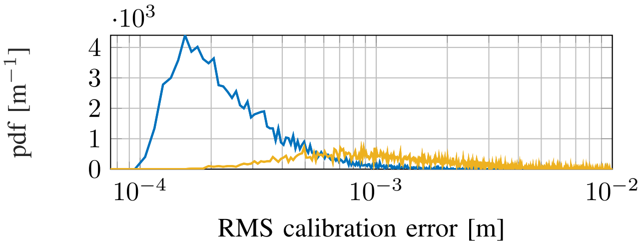
When readings from a low-cost sensor S_1 are compared against the intermediate calibration model and stored as $\hat{\mathcal{D}}$, the overall calibration model becomes influenced by the model uncertainty associated with the intermediate calibration:

$$\hat{y}_3 = \mathbb{E}(\hat{f}_{1\to3}(y_1)) = g(y_1, \text{cov}(\hat{f}_{2\to3}), \mathcal{D}, \hat{\mathcal{D}}), \tag{2}$$

where $\hat{y}_3$ represents the expected true position of the mechatronic system based on the reading of the low-cost sensor S_1, taking into account the variance of the intermediate calibration model. This expression can be evaluated in real-time to correct for repeatable sensor inaccuracies, providing an improved estimation of the true position.

C. Simulation Results

The simulation involves conducting Monte Carlo simulations with a total of 5000 scenarios. In each scenario, the calibration models $f_{1\to2}$ and $f_{1\to3}$ are randomly generated using a Fourier basis. The figure below presents a comparison between the calibration errors $\|\hat{y}_3 - y_{\text{true}}\|_2/\sqrt{N}$ obtained from the proposed calibration approach (blue) and a lookup table with linear interpolation (yellow). In this normalized empirical probability density function plot, a better performance corresponds with more probability mass being concentrated to the left of the figure.



The results clearly demonstrate the superior accuracy of the developed calibration approach for two main reasons: (i) The chosen model structure is better suited for extrapolation, improving accuracy beyond the measured data range, and (ii) considering the model uncertainty of the intermediate calibration model gives more weight to prior information in these regions. Consequently, the developed approach surpasses the lookup table method, significantly enhancing calibration accuracy.

D. Conclusion

The developed cascaded calibration method offers an effective solution for mitigating position sensor inaccuracies in mechatronic systems. By accurately modeling and calibrating the sensors in a cascaded manner, the method achieves enhanced calibration accuracy while minimizing resource requirements. This approach enables more precise calibration of mechatronic systems, even with limited resources, thereby improving their overall performance.

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