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Supervised Self-Calibration for Fault-Tolerant xMR-Based Angular Decoders under Dynamic Perturbations

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Summary:

This paper introduces a self-calibration methodology inspired by biological systems, focusing on its application in xMR angular decoders. Designed to address the limitations of static calibration, the approach effectively corrects mechanical misalignments and operational deviations. By leveraging simulated and empirical data to train machine learning (ML) models such as support vector regression (SVR), convolutional neural networks (CNN), and resource-allocating networks (RAN) with radial basis function (RBF) components, it enables real-time error compensation. Experimental results demonstrate a reduction in mean absolute error (MAE) from 2.06° to 0.08° and confirm a significant improvement in recovery efficiency, robustness, and reliability.

Keywords: Self-Calibration, TMR sensor, CNN, SVR, RAN.

Introduction

The ongoing advancement of sensor technology has led to an increase in the number and variety of low-cost, compact, and portable sensors on the market [1], establishing them as the foundation for real-time measurement, monitoring, and data analysis in key areas of Industry 4.0. However, the accuracy and reliability of data generated by these sensors can raise concerns, particularly in the absence of proper calibration [2]. Static calibration approaches, while initially effective, often fail to account for factors such as sensor degradation, environmental variability, and mechanical impacts, necessitating the development of more advanced methods [3]. Inspired by self-maintenance in living organisms, this research proposes a self-calibration approach as part of a broader self-X system, enhancing reliability and autonomy [4]. Although the self-calibration itself is static, the approach facilitates real-time error compensation by applying pre-trained models to dynamic data. This article compares supervised self-calibration methods, emphasizing ML-based models such as artificial neural networks, and their comparison with traditional methods like linear regression. Their effectiveness is evaluated in terms of enhancing fault tolerance and reliability under diverse dynamic perturbations [5].

Proposed Methodology

The proposed methodology employs a mathematical model to simulate sensor output signals under varying operational conditions, including both ideal scenarios and that representative of real-world distortions. By incorporating both simulated and real data, the methodology ensures comprehensive coverage of potential sensor behavior. ML models were trained using these datasets, with reference values serving as targets to guide the calibration process. The effectiveness of training was evaluated using key metrics: mean squared error (MSE) to measure prediction accuracy and the coefficient of determination (R^2) to assess the model's ability to describe data variability [5]. To implement the self-calibration process, algorithms such as SVR, CNN, and RAN were selected. The raw data was processed directly, without pre-extracted features. Additionally, trained CNN layers were used to generate high-level features. These frozen feature layers (FL) produced characteristics of the data, which were then fed into the RAN and SVR algorithms, replacing the standard fully connected layer typically used at the top of the CNN architecture. This approach allowed for a comparison of the effectiveness of using raw data versus high-level features generated by CNN.

Results

The study utilized both simulated and real-world data. Simulated data consisted of synthetically generated tunnel magnetoresistive (TMR) sensor outputs with injected errors, including phase shifts, amplitude imbalance, noise, and offset, allowing for an in-depth examination of self-calibration responses to various types of distortions and their combinations (Fig. 1).

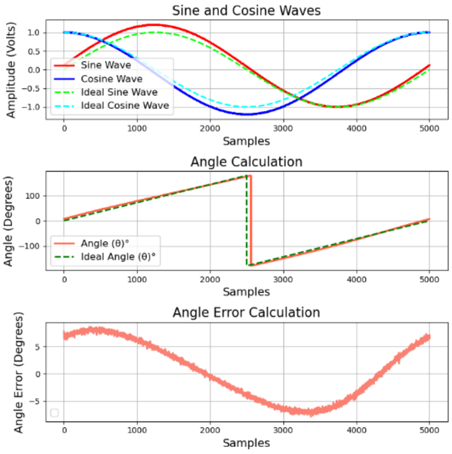

Fig. 1. Simulated ideal and corrupted TMR sensor outputs (10% amplitude imbalance, 1° phase shift, ±0.1 V offset, and 0.005 V noise).

Empirical data were collected using the experimental setup shown in Fig. 2, designed to simulate and introduce a variety of mechanical errors.

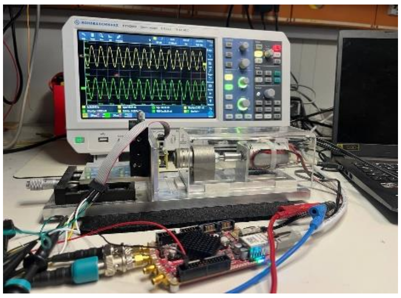

Fig. 2. Lab setup with fault injection capability.

Figure 3 shows TMR sensor outputs after displacements along the X, Y, and Z axes (10 mm, 15 mm, and 10 mm), simulating operational failures. The subplots illustrate sensor outputs, calculated versus reference angles, angle errors before and after calibration (with reduced residuals), and the error distribution shifting toward zero post-calibration. The dataset comprised 208,629 samples, randomly split into 80% for training (166,903 samples) and 20% for testing (41,726 samples). The results in Tab. 1 are averaged over 10 independent runs to ensure reliability and robustness, with standard deviations included for clarity. MAE represents the angular error after self-calibration. The hierarchical method, which integrates frozen CNN feature layers with RAN and SVR, significantly outperformed the direct application of these models, reducing the initial angle error from 2.06° to 0.08°. In RAN, 10 centres were used, while SVR utilized 6,407 support vectors. These results confirm the effectiveness of self-calibration in improving accuracy and reliability under dynamic perturbations. Future work will aim to develop adaptive and dynamic calibration methods for real-time error correction and improved sensor accuracy across varying operational scenarios.

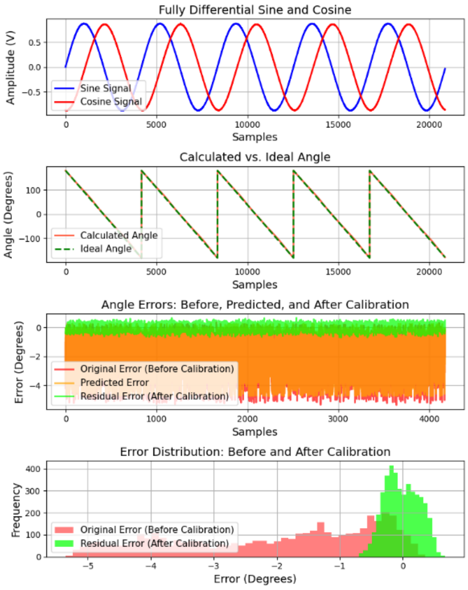

Figure 3. TMR outputs before/after calibration.

Tab. 1: Model evaluation results

Method	MSE [°²]	R²	MAE [°]
CNN	0.02 (0.005)	0.99 (0.002)	0.11 (0.013)
SVR	0.05 (0.0002)	0.98 (0.0001)	0.18 (0.0008)
RAN	0.16 (0.053)	0.93 (0.022)	0.31 (0.061)
SVR (FL)	0.01 (0.0003)	0.99 (0.0001)	0.10 (0.0007)
RAN (FL)	0.01 (0.0011)	0.99 (0.0024)	0.08 (0.004)

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