APPLICATION OF REINFORCEMENT LEARNING AI METHODS FOR SELF-CALIBRATION OF MODULAR OPTICAL ROTARY ENCODERS

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Abstract. The study explores the application of semi-supervised deep learning models for the self-calibration of modular optical rotary encoders, aiming to minimize dominant mechanical installation errors and enhance measurement accuracy. Reinforcement learning (RL) as semi-supervised deep learning models are employed to extract key features from cross-calibration data collected from the developed modular encoder, which integrates multiple optical sensors. These models facilitate the identification of critical patterns within the data, enabling the construction of structured and well-defined learning procedures tailored for the calibration process. The proposed RL framework leverages real-time feedback to adaptively adjust the encoder's readings based on performance metrics derived from the calibration data. This iterative learning process significantly improves the encoder's reliability under diverse operating conditions, making it more resilient to variations. By enhancing self-calibration and optimizing both the number and arrangement of optical sensors, this research paves the way for more robust and precise measurement systems. The obtained results demonstrated a significant reduction in installation errors, leading to the respective improvements in measurement accuracy. These findings showcase the potential of AI-driven approaches in advancing optical encoder technology, indicating that the integration of reinforcement learning opened additional room for enhancements in performance across various high-demand applications.

Keywords: self-calibration; optical rotary encoder; reinforcement learning; deep learning.

Introduction

Modular optical rotary encoders are critical components in precision measurement systems in various industries where accurate angular position measurements are needed [1]. The accuracy of the encoders is required to be at least 10 times higher than that of the respective machines they are installed and work [2]. It was demonstrated that the accuracy is dependent on some details of the encoder's design [3]. Some errors, like those attributed to temperature changes, could be compensated [4]. However, mechanical installation errors such as eccentricity [5] and inclination increase measurement errors [6]. Traditional calibration methods [7] are precise under laboratory conditions, but this accuracy often deteriorates when encoders are used in dynamic operational environments due to mechanical installation errors and different work conditions. Several advanced techniques have been proposed to enhance encoder accuracy. Jia et al. developed FE-GABPNN, which combined Fourier analysis and neural networks optimized by genetic algorithms to compensate for temperature induced errors [8]. Kim et al. introduced an encoder implementation, which utilized a self-calibration equal-division-average (EDA) method [9], while Zhao et al. proposed ELM-FNN, which enabled fast error testing and compensation for optical encoders [10]. However, some of these methods depend on predefined models and may struggle with changing conditions.

Reinforcement learning (RL) has become an effective approach for calibration problems in various systems and applications without needing explicit error modelling [11; 12]. Unlike static calibration methods, RL could enable continuous adaptation to varying operational conditions and improve sensor reading accuracy. Recent studies have highlighted the potential of RL in continuous control tasks. The Deep Deterministic Policy Gradient (DDPG) reinforcement learning algorithm, an actor-critic method, can enable real-time sensor calibration in continuous action spaces [13]. The Twin Delayed DDPG (TD3) algorithm addresses limitations in standard DDPG by incorporating clipped double Q-learning and delayed policy updates improving stability [14].

This study investigates RL for self-calibration of modular optical rotary encoders. A framework is proposed that leverages multiple optical sensors within a modular encoder configuration and a RL model that is based on DDPG architecture enabling learning policies for encoder calibration. The system observes sensor readings, applies calibration adjustments, and receives feedback based on measurement accuracy, learning and optimizing encoder accuracy.

Materials and methods

This section outlines the modular optical rotary encoder experimental setup, procedure for collecting the data, reinforcement learning environment to model the calibration process, training and evaluation.

Experimental Setup

The experimental setup consisted of a modular optical rotary encoder with six optical sensors (S1-S6) positioned around the stator. Each sensor was placed at a specific angular position relative to sensor S1, which served as the reference point of 0°. The nominal angular positions of the remaining sensors were as follows: S2 at 90°, S3 at 120°, S4 at 180°, S5 at 240° and S6 at 270°. This multi-sensor configuration provided ability to collect measurements for the calibration process, allowing the system to possibly learn relationships between different sensors.

The test encoder was mounted on an angular comparator system equipped with a high-precision optical encoder that served as the reference standard. This reference encoder provided ground-truth measurements with significantly higher accuracy than the test encoder. Both encoders were mechanically coupled to synchronize rotation during data collection. This configuration allowed for precise measurement of angular deviation errors across the full rotation range of 360°.

Data Collection

During the data collection phase, both the test encoder and the reference encoder were rotated through a complete 360° cycle. Position readings were recorded from the reference encoder and all six sensors of the test encoder at regular intervals. Due to the reference encoder being incremental, its readings were not tied to absolute angular positions. Because of this, the recorded reference data was aligned with the sensor S1 readings by removing the offset and setting the first reference value equal to the first S1 position.

The difference between the reference encoder position and each sensor reading was calculated to determine the measurement error for each sensor at each angular position. This error data was the basis for both training and evaluating the reinforcement learning model. The error calculation for S1 was straightforward as the reference encoder data was tied to its position, while for the remaining sensors (S2-S6), their initial offset was accounted from the S1 sensor position when calculating the errors.

The initial measurement errors of all six sensors (S1-S6) before calibration in the test encoder are presented in Figure 1.

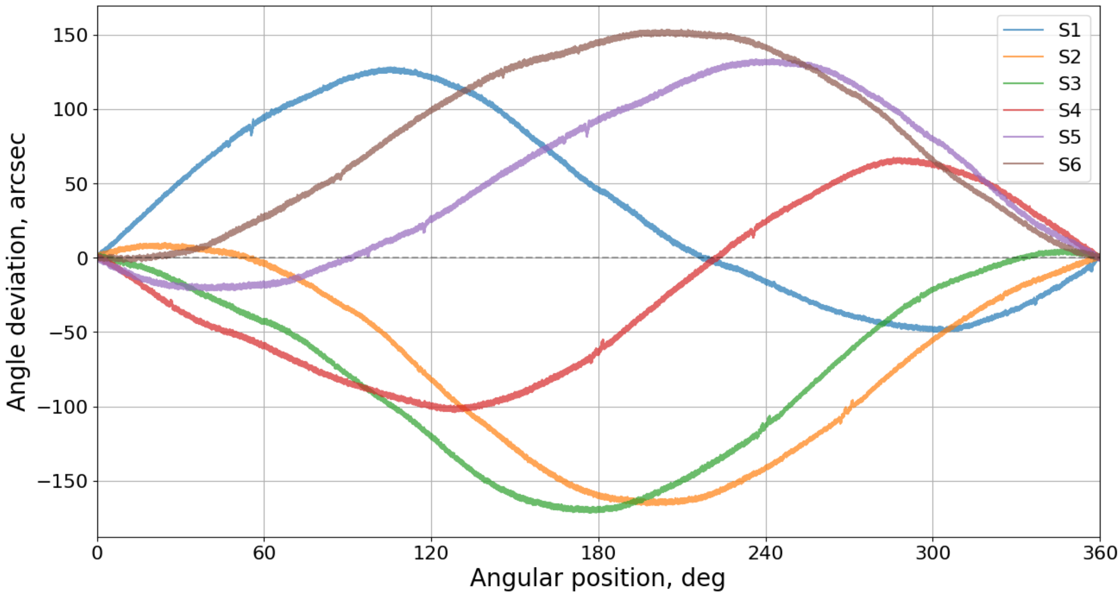

Fig. 1. **Modular optical rotary encoder sensor angle deviations**

The errors exhibit sinusoidal patterns with varying amplitudes and phase shifts, indicating system angle deviations likely caused by mechanical installation errors such as eccentricity, inclination and possibly other high-frequency errors (vibrations, temperature).

Reinforcement Learning Methods

A custom calibration environment was developed to model the sensor calibration process as a RL task. This environment processes raw encoder sensor data and provides a framework for an RL agent to learn optimal calibration adjustments. The state of the environment holds the current sensor readings and associated errors, while actions represent calibration adjustments applied to sensor readings.

The state space was designed to hold relevant information for the self-calibration process, consisting of 18 features:

- Current readings from all six sensors.
- Previous readings from all six sensors.
- Current error values for all six sensors.

All state values were normalized to the range [-1, 1] to ensure stable learning. Angle values were divided by 360°. The action space was defined as continuous adjustments to sensor readings that were constrained to ± 0.05° (180 arcseconds) per step for each sensor. This constraint ensured that the calibration process remained stable and prevented excessive adjustments.

The RL algorithm self-calibration precision is highly dependent on the design of the reward function. This function in the calibration environment was designed to minimize sensor measurement errors, while ensuring measurement stability. It included an error reduction reward, and an action penalty to discourage model excessive corrections. The final reward function was a weighted sum of these components (1)

$$\text{reward} = 2.0 \times \text{improvement} + 0.1 \times \text{action\_penalty}\,. \tag{1}$$

The DDPG algorithm was used for the calibration task. DDPG is appropriate for continuous control problems with continuous action spaces. Because of this it was chosen for the calibration adjustments required for the modular encoder. The DDPG architecture was configured with an actor network (policy) and a critic network (Q-function). The actor network was developed with three hidden layers of 512 neurons each with rectified linear unit (ReLU) activation functions. This actor network maps states to actions. The critic network which is responsible for estimating the expected return of a specific action in each state also had three hidden layers with 512 neurons each and ReLU activation functions.

The developed model used only raw data gathered from the sensors, so that no statistical processing of the results was performed.

Results and discussion

The collected data from each of the 6 sensors was used to train the DDPG reinforcement learning model for encoder calibration. The model buffer was set to 100,000 which was the number of data points collected for one 360° encoder revolution. The model was trained for 50,000 timesteps. The error profiles of the sensors before and after calibration are presented in Figure 2. The model yielded significant improvements in reducing angle deviation errors for all six sensors.

The comparison between baseline and calibrated measurement errors is presented in Table 1. The DDPG model achieved an overall mean absolute error (MAE) improvement from 67.2 arcsec without calibration to 10.91 arcsec with calibration, which resulted in an 83.2% improvement in measurement accuracy. Sensor S1 had the biggest improvement of 93.5% reducing the baseline MAE from 56.48 arcsec to 3.68 arcsec. Similar results can be seen for sensors S2, S3, S4 and S6. Sensor S5 had the smallest improvement of 55.3%, which could suggest that there are sensor specific characteristics that limited calibration effectiveness in that position of the encoder.

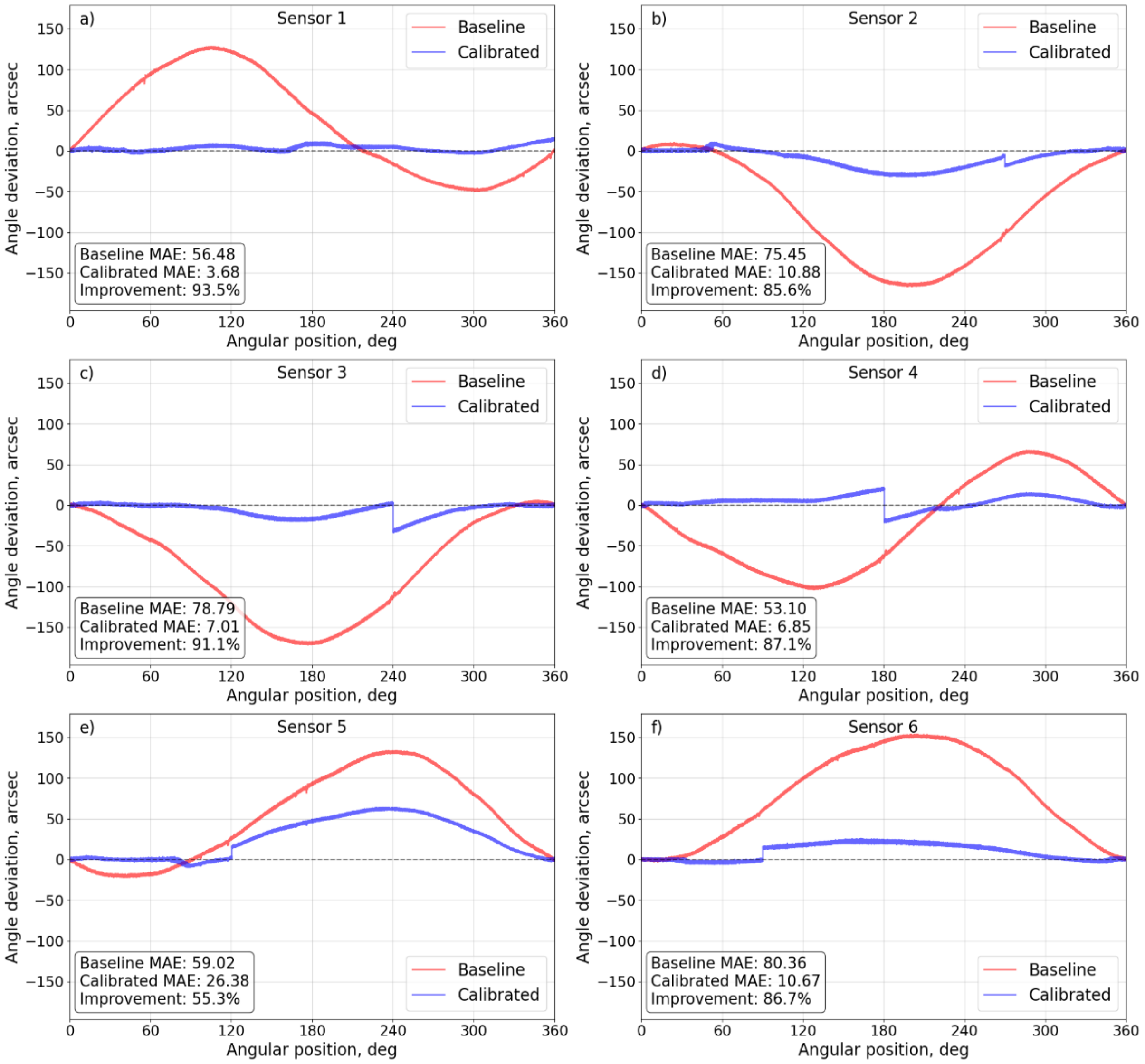

Fig. 2. **Calibrated measurement error comparison**

Table 1

Comparison of mean absolute error (MAE) between baseline and calibrated encoder errors

Sensor	Baseline MAE, arcsec	Calibrated MAE, arcsec	Improvement MAE, %
S1	56.48	3.68	93.5
S2	75.45	10.88	85.6
S3	78.79	7.01	91.1
S4	53.10	6.85	87.1
S5	59.02	26.38	55.3
S6	80.36	10.67	86.7
Overall	67.20	10.91	83.2

The DDPG model achieved an 83.2% reduction in overall MAE, which is comparable to advanced calibration methods for optical rotary encoders [1-3] and exceeds the performance of traditional approaches. The RL-based method advantage is that it can compensate for position-specific error patterns without requiring explicit error modelling. The residual MAE of 10.91 arcsec (≈ 0.003°) was achieved without specialized calibration equipment beyond an initial reference encoder, highlighting its practical applications.

Conclusions

This study shows that the Deep Deterministic Policy Gradient (DDPG) algorithm-based reinforcement learning model can calibrate modular optical rotary encoders, improving measurement accuracy by 83.2% and achieving a calibrated overall accuracy of 10.91 arcsec. The model compensates for mechanical installation errors like eccentricity and inclination while maintaining stability. Further research is needed to improve performance for certain sensor positions, particularly by testing the system with different variations of high frequency errors.

Author contributions

Conceptualization, A.P.; data curation, M.R.; formal analysis, D.G. and M.R.; methodology, D.G.; software, P.O.; validation, D.G. and M.R.; investigation, A.P. and P.O.; writing – original draft preparation, A.P.; writing – review and editing, D.G., P.O., and M.R.; visualization, P.O.; supervision, A.P.; project administration, n/a; funding acquisition, n/a. All authors have read and agreed to the published version of the manuscript.

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