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Improvement of distance measurement accuracy for CMMs equipped with video probe based on correction of the error related to measurement direction vector

Wiktor Harmatys[1], Adam Gąska[1], Piotr Gąska[2], Maciej Gruza[1]

[1] Laboratory of Coordinate Metrology, Cracow University of Technology, al. Jana Pawła II 37, 31-864 Cracow, Poland
[2] Department of Manufacturing Systems, Faculty of Mechanical Engineering and Robotics, AGH University of Science and Technology, al. Mickiewicza 30, 30-059 Krakow, Poland

wiktor.harmatys@pk.edu.pl

Abstract

In this study, an extended analysis of measurement errors of optical coordinate measuring machines (OCMMs) is presented with the focus on the impact of the direction vector of the measurement point on the form errors. A specially designed rotary table with a central through hole is used in the experiments presented in the paper. It enables precise optical measurements using transmitted light. The calibration procedures for both optical and contact probes are conducted on the same setup to ensure consistency. Subsequently, the measurement errors across various angular orientations is determined, generating a correction matrix based on the direction vector of the measurement point.

Once the error matrix is established, it is applied to the measurement of geometric features of optical standards, specifically a reference glass plate with circles. Following this, the matrix is used also to measure complex industrial components, including plastic and metal parts of known geometry that have been previously calibrated on other coordinate measuring machine - PMM 12106. These components feature intricate geometric characteristics, such as key dimensions, flatness, lines, circles, circle segments, and parallelism, all of which are measured in this study.

The aim is to evaluate how the application of the correction matrix affects the precision of the measurements, particularly when dealing with parts of varying material properties and complex shapes. The results of the experiment provide insight into the potential improvements in measurement accuracy when using direction vector-based corrections, highlighting the effectiveness of this approach for enhancing optical measurement techniques in industrial environments.

CMM, accuracy, optical measurement, video probe

1. Introduction

In modern manufacturing industries, the demand for precision and repeatability in geometric measurements continues to grow, particularly in sectors such as automotive, aerospace, and medical technologies. The quality and reliability of products in these industries heavily depend on the ability to accurately reproduce the designed dimensions of components. Coordinate Measuring Machines (CMMs) play a pivotal role in ensuring the quality control of these components by verifying their geometric properties against design specifications. A specialized class of these devices, Optical Coordinate Measuring Machines (OCMMs), leverages optical probes to enable non-contact measurements, proving indispensable when handling delicate, soft, or transparent materials where traditional tactile probes may cause surface damage or introduce measurement errors. Despite their numerous advantages, OCMMs are inherently susceptible to specific types of measurement errors due to technological limitations and the optical systems' operational characteristics. The sources of these errors can range from geometric inaccuracies of the machine itself to environmental influences such as temperature fluctuations or vibrations. Recent developments in artificial intelligence (AI) and machine learning (ML) offer promising opportunities to enhance measurement accuracy by identifying and correcting these errors. Techniques such as error modeling, correction matrices, and predictive algorithms have been successfully integrated into various precision measurement applications, including CMMs and OCMMs [1-3,5]

AI-driven methodologies have shown potential in not only automating data analysis but also in providing real-time corrections to measurement processes. For instance, ML algorithms can be employed to analyze the relationships between measurement parameters and observed deviations, thus facilitating the development of compensation models that adjust measurement results based on identified standards. Furthermore, integrating AI into metrology has been instrumental in the certification and validation of measurement algorithms, enhancing the reliability of the results in industrial settings [4].

In this paper such example of use of AI in coordinate metrology is given. Direction-dependent measurement errors of CMMs equipped with video probe are identified and then, using AI-based model that is described in following sections of the paper, corrected during measurements.

2. Data Processing and Neural Network Training

The process of improving measurement accuracy using neural network-based corrections required a meticulously designed data processing and model training pipeline. This section details the methodologies employed for data acquisition, preprocessing, integration, and the subsequent training of the neural network.

2.1. Data Acquisition and Preprocessing

The initial stage involved gathering measurement data from calibration standards. The datasets consisted of point coordinates (X, Y, Z), direction vectors (i, j, k), and deviations (dev i, dev j, dev k) recorded during measurements. These measurements were performed using an optical coordinate measuring machine (OCMM) Zeiss O'Inspect with an additional special designed rotary table, which introduced angular variations that were systematically recorded.

Each dataset was subjected to preprocessing to ensure consistency and accuracy in the subsequent stages. The preprocessing steps included the calculation of distances between measurement points, derived from feature identifiers specified in the measurement configuration files. Additionally, for circular standards, the least squares method was applied to fit circles to the point data, allowing for the calculation of circle centers, diameters, and form errors. The resulting geometric parameters served as critical inputs for model training.

2.2. Data Integration and Filtering

Following the preprocessing of individual datasets, the data were integrated into a unified structure. This integration involved combining measurements from standard circles and glass scale into a single dataset, ensuring a comprehensive representation of various measurement scenarios.

To enhance the quality of the data used for training, a multi-step filtering process was applied. First, the data were segmented into angular intervals based on the direction vectors. Each interval was analyzed for outliers using statistical techniques such as the two-sigma. Additionally, the data have been filtered to retain a specific number of points, which is 10 000, to balance the dataset size with computational efficiency.

A crucial part of the filtering process involved ensuring uniform distribution across angular intervals to prevent bias in the training data. The filtered data were sorted in ascending order based on the angular measurements, facilitating a structured input format for the neural network.

2.3. Data Normalization

Before training the neural network, the input features were normalized to improve the model's learning efficiency and convergence rate. Z-score normalization was applied to the direction vectors (i, j, k) transforming them to have a mean of zero and a standard deviation of one. This standardization was essential for ensuring that the neural network treated all input features with equal importance, avoiding dominance by any single feature due to scale differences.

Normalization also played a critical role in preventing issues related to numerical instability during training, particularly when dealing with high-precision measurement data typical in optical metrology.

2.4. Neural Network Architecture and Training

The neural network was designed to predict measurement errors based on the normalized direction vectors. The model architecture consisted of multiple layers with varying numbers of neurons, optimized for both performance and computational efficiency. To prevent overfitting, regularization techniques such as dropout were employed, where a fraction of neurons was randomly deactivated during training to improve generalization.

The model was compiled using the RMSprop optimizer, known for its effectiveness in handling non-stationary objectives, which is typical in measurement data due to varying geometries and environmental conditions. The loss function used was Mean Squared Error (MSE), chosen for its ability to penalize larger deviations more heavily, thereby focusing the model on minimizing significant errors.

During training, early stopping criteria were implemented to halt the process if no improvement was observed in the validation loss over a set number of epochs. This approach ensured efficient use of computational resources and prevented unnecessary overfitting.

2.5. Model Evaluation and Validation

The trained model was evaluated using a separate test dataset, comprising measurements not included in the training phase. The model's performance was assessed by comparing the predicted corrections to the actual measurement errors. The corrected distances were calculated by subtracting the predicted errors from the original measured distances, and these corrected values were compared against nominal distances.

Statistical analyses, including error distribution histograms and summary statistics, were generated to visualize the effectiveness of the corrections. The model's ability to reduce measurement errors across different geometries and angular positions was critically analyzed to identify strengths and areas for further improvement.

3. Results

In the subsequent phase of the research, an additional glass standard was employed to validate the effectiveness of the neural network-based correction method. Measurements were conducted using an optical coordinate measuring machine (OCMM) equipped with an optical probe at a maximum magnification of 6.4x. The measurements focused on a glass standard comprising nine distances, evaluated across multiple angular settings (132.97°, 193.49°, 230.89°, and 302.98°) (Fig.1). For each angular configuration, 30 repeated measurements were performed to ensure statistical robustness.

Following data acquisition, comprehensive statistical analyses were conducted on all measured distances. Subsequently, the correction algorithm, developed in the neural network training phase, was applied to the measured data. The resulting corrections were integrated into the original measurements, and post-correction analyses were performed to evaluate the effectiveness of the applied adjustments.

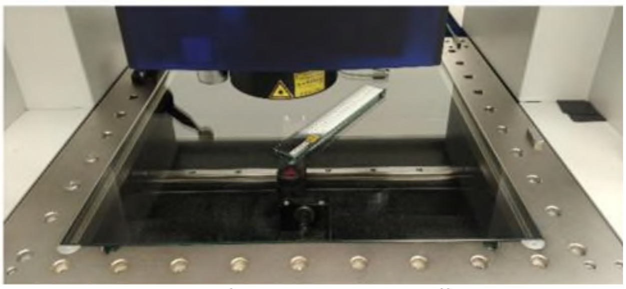

Figure 1 Measurements of the glass standard in different orientations

Analysis of Corrected Measurements

Table 1 summarizes the statistical results obtained before and after applying the corrections. The data reveal that for shorter distances, such as 2.0482 mm, the average errors after correction exhibit minimal deviation compared to the pre-correction values. However, a significant 72% of the individual measurements demonstrated improvement, indicating the neural network's effectiveness in refining measurement accuracy for short lenghts.

For longer distances, such as 14.3359 mm and 16.3837 mm, the average measurement errors before correction were more negative (-0.00010 mm and -0.00006 mm, respectively). These deviations likely stem from the cumulative geometric errors of the OCMM. The introduction of neural network-based corrections resulted in these errors shifting closer to zero (-0.00009 mm and -0.00005 mm, respectively). This suggests that the correction algorithm effectively compensates for systematic deviations even in longer measurements. However, it is noteworthy that the percentage of improved measurements decreases with increasing distance. This trend aligns with the understanding that longer distances are more susceptible to additional influencing factors, such as machine geometry imperfections, thermal disturbances, and slight optical misalignments, which complicate the correction process.

Furthermore, the conducted analyses indicate that the standard deviations (std) before and after correction remain relatively unchanged across all measured distances. This observation suggests that the applied corrections primarily affect the systematic error components—shifting the mean values closer to zero—without significantly altering the dispersion of the measurement results. The consistency of standard deviation values implies that while the corrections enhance measurement accuracy, they do not impact the inherent repeatability of the measurements. This stability in measurement dispersion is advantageous, as it confirms that the correction process does not introduce additional variability, maintaining the repeatability of the measurement system.

Table 1 Results of the measurement before and after correction. IR denotes 'Improvement Rate'

Nominal / mm	*Min (before) / mm*	*Max (before) / mm*	*IR / %*	*Min (correction) / mm*	*Max (correction) / mm*
2,0482	*-0,00110*	*0,00093*	*72*	*-0,00105*	*0,00086*
4,0961	*-0,00111*	*0,00088*	*58*	*-0,00106*	*0,00084*
6,1441	*-0,00118*	*0,00083*	*66*	*-0,00113*	*0,00080*
8,1917	*-0,00128*	*0,00112*	*63*	*-0,00123*	*0,00108*
10,2399	*-0,00127*	*0,00091*	*60*	*-0,00122*	*0,00088*
12,2876	*-0,00125*	*0,00116*	*47*	*-0,00120*	*0,00112*
14,3359	*-0,00158*	*0,00095*	*60*	*-0,00153*	*0,00091*
16,3837	*-0,00118*	*0,00082*	*67*	*-0,00113*	*0,00079*
18,4317	*-0,00106*	*0,00098*	*55*	*-0,00102*	*0,00095*

The presented histogram illustrates the distribution of measurement errors before and after applying neural network-based corrections in optical coordinate measurements. The original measured errors, represented by the blue bars, exhibit a broader distribution compared to the corrected errors, which are denoted by the orange bars. The histogram is further supplemented by red dashed lines marking the ±0.0004 threshold, which serves as a reference for evaluating measurement precision.

The application of corrections results in a noticeable centralization of errors around zero. This centralization indicates that the neural network effectively mitigates systematic biases inherent in the measurement process. The corrected data demonstrate a higher concentration of values near the center of the histogram, signifying that the majority of measurements have been adjusted to reduce deviations from the nominal values. The increased frequency of errors within the ±0.0004 threshold after correction suggests an overall enhancement in measurement precision. This improvement is evidenced by the densification of corrected errors in the central region of the histogram, which contrasts with the wider spread observed in the uncorrected data.

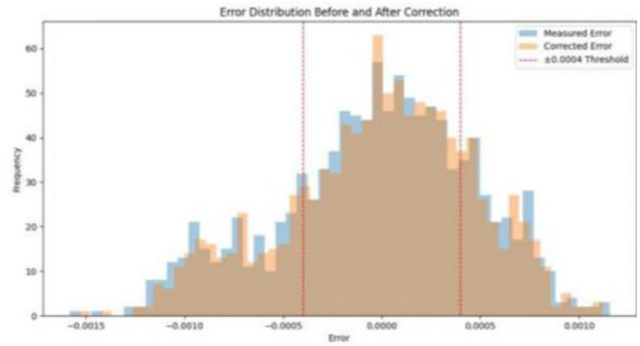

Figure 2 Histogram with errors before and after correction

Despite these improvements, both the corrected and uncorrected datasets exhibit points extending beyond the defined threshold, indicating the persistence of larger errors. However, the points in the corrected data are less pronounced, reflecting a reduction in the occurrence of extreme deviations. This reduction highlights the neural network's ability to address more systematic errors.

An additional observation pertains to the symmetry of the error distribution. The uncorrected measurements display slight asymmetry, with a bias towards negative deviations. Following correction, the distribution becomes more symmetric around zero, suggesting that the neural network successfully compensates for these directional biases.

Furthermore, the histogram reveals a decrease in the number of measurements exceeding the ±0.0004 threshold after correction. This reduction underscores the efficacy of the correction algorithm in enhancing measurement accuracy. However, the impact of the corrections is more pronounced near the center of the distribution, while extreme deviations are less affected, indicating potential limitations of the correction model in handling certain types of errors.

In conclusion, the histogram analysis confirms that the neural network-based correction significantly improves the accuracy of optical coordinate measurements. The corrections primarily reduce systematic errors, shifting the distribution towards zero and increasing the proportion of measurements within acceptable error limits. Although the corrections effectively minimize moderate deviations, they do not completely eliminate outliers, suggesting that additional factors, such as environmental influences or machine-specific geometric imperfections, continue to affect measurement accuracy. These findings validate the integration of AI-based correction algorithms into OCMM systems as a means to enhance precision in industrial quality control applications.

4. Conclusion

The results presented in Table 1 highlight the neural network's capacity to systematically improve measurement accuracy by reducing the average error across various nominal distances. Notably, shorter distances exhibit higher improvement rates, suggesting that the correction model performs optimally for shorter lenghts. Conversely, for longer distances, although the improvement rates are slightly lower, the corrections still demonstrate a meaningful reduction in systematic errors.

The consistent standard deviations before and after correction reinforce the hypothesis that the neural network primarily addresses systematic measurement deviations rather than random noise or variability inherent in the measurement process. This behavior is advantageous in industrial applications where consistent, repeatable measurements are critical for quality assurance.

In conclusion, the integration of neural network-based corrections in OCMM systems has proven to enhance measurement accuracy, particularly in addressing systematic directional errors. While the improvements are more pronounced in shorter measurements, the methodology exhibits a robust capacity to compensate for deviations across a range of measurement lengths, underscoring its potential for broader industrial application.

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