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Training efficient and compensating fast: Data augmentation for thermal error compensation models of machine tools.

Sebastian Lang[1, 2], Nico Lampert[1], Josef Mayr[2], Konrad Wegener[2], Markus Bambach[1]

[1] *Advanced Manufacturing Lab ETH Zurich, Technoparkstrasse 1, 8005 Zurich, Switzerland*
[2]*inspire AG, Technoparkstrasse 1, 8005 Zurich, Switzerland*

selang@ethz.ch

Abstract
The increasing importance of sustainability in manufacturing has created a trilemma situation between resource efficiency, productivity and precision. As the relevance of thermal errors increases with the shift to less cooling-reliant manufacturing approaches, compensation models for thermal errors have been proposed as a possible solution to the described trilemma. Since those data-driven compensation models are heavily reliant on both data amount and data quality, this paper aims at investigating different approaches of preprocessing and potentially augmenting the input data for compensation models. This allows for a higher sampling frequency than that of the employed measurement cycle and makes more data points available for training. The employed LASSO ARX model can reduce the volumetric error by more than 71 %. The use of data augmentation represents an increase of around 20 percentage points in volumetric accuracy at a higher sampling rate and a higher efficacy than just adding additional noisy data.

Data augmentation, Thermal error compensation, Machine Tools, Upsampling

1. Introduction

Thermal errors are one of the largest challenges for sustainable and high precision production using machine tools (MTs) [1]. Thermal error compensation promises an energy efficient solution if the amount of required training data is small [2]. For this data driven models allow for an adaptive and self-learning thermal error compensation [3–5]. Zimmermann et al. [6] demonstrated the effectiveness of thermal error compensation applied to an impeller workpiece reducing the thermal error by up to 73% on the workpiece. Kaftan et al. [7] employed two model strategy to compensate fast acting effects on thermal errors of working space condition change in Swiss-type lathes. Abdulshahed et al. [8] used a thermal imaging camera for modelling thermal errors based on grey models. Chengyang et al. [9] used infrared images to compensate for the thermal expansion of a spindle using deep learning methods. To increase the amount of available data they augmented the data using flipping and cropping to get 3.5 times as much data as measured. Data augmentation for time series is less common compared to computer vision approaches, largely due to the difficulty of relating features to one another [10]. Oh et al. [11] showed that interpolation is a suitable augmentation strategy that increases model accuracies by almost 2% over many types of different datasets. It is crucial that the continuity of the data is ensured [12], which is especially important for thermal errors which are a continuous phenomenon with typically pronounced hysteresis effects [13].

One of the key drawbacks of data driven compensation methods, its data hunger could be slightly alleviated using data augmentation and higher sampling strategies.

2. Methods

The proposed compensation model with different data augmentation techniques and the experimentally investigated MT are described as well as the utilised compensation architecture.

2.1. Data augmentation for thermal compensation models

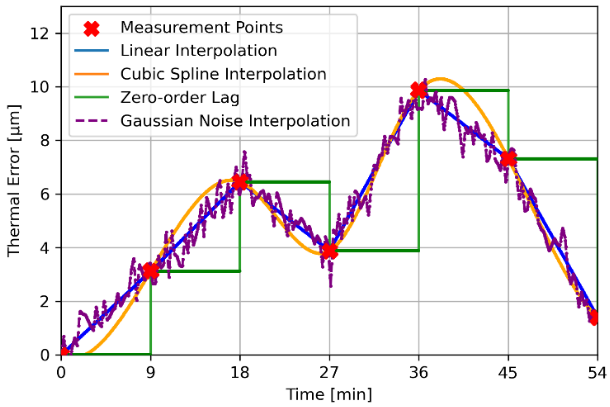

Figure 1. Visualization of the different interpolation strategies for 5 measurement points of a thermal error.

Figure 1 shows the augmentation approaches which were investigated for up-sampling the thermal error measurements: linear interpolation, cubic spline interpolation. Furthermore, as a comparison, the down-sampled temperature data is also analysed which can be compared to a zero-order lag model of the thermal error. This only measures the temperatures whenever there is an error measurement and keeps both values constant subsequently. This means that the model is used at a significantly lower frequency, reducing the computational cost but also introduces a delay from thermal behaviour until the compensation can react.

2.2. Experimental setup

To compare the different data augmentation approaches, a 200-hour experiment was conducted on a DMG Mori NTX2000, a multi axis mill-turn machining centre shown in Figure 2. During the experiment, the data of 45 temperature sensors was collected every two seconds and sampled to every 30 seconds. Furthermore, different load cases with a duration of five minutes were performed between each error measurement of the MT moving all axes and spindles at random speeds and intervals. The measurement cycle requires around 250 seconds.

The measurement cycle measures a measurement sphere placed on the clamping jaw of both turning spindles. The position of the sphere is measured using a touch trigger probe. And the volumetric error is subsequently determined.

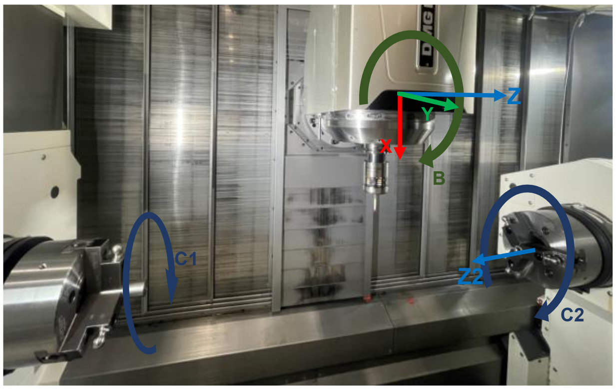

Figure 2. Kinematics of the NTX2000 with the used touch trigger probe and measurement artefacts mounted on the spindle jaws. The highlighted axes are the positioning axis of the MT.

2.3. Model setup

In order to generate a robust compensation model a Lasso regression with an time dependent ARX model is carried out. This allows the selection of the model parameters and model inputs at the same time. Similar models were introduced by Zimmermann et al. [5] and Lang et al. [2].

3. Results

Figure 3 shows the volumetric error of the spindle 1 with and without compensation. The root mean square error (RMSE) of the uncompensated thermal error of 81 µm is reduced to 23.6 µm after compensation which corresponds to a reduction of 70.9 %.

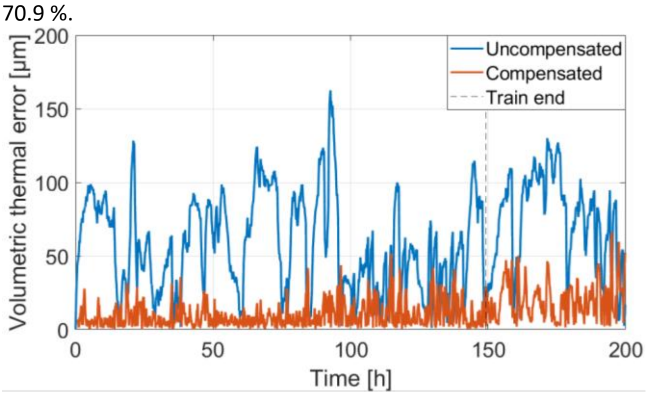

Figure 3. Volumetric thermal error of the spindle 1. Linear Sampling of the error

Table 1 Reduction of the volumetric RMSE on the validation data

Interpolation Approach	*Reduction*	*With gaussian noise*
Original sampling	49.4 %	51.1 %
Linear	70.9 %	71.3 %
Cubic Spline	71.2 %	71.5 %

Table 1 shows the different reductions of the RMSE of the volumetric error due to the same compensation model. It can be observed that the original sampling performs the worst as the lowest number of data points are available. Increasing the number of data points, which increases the sampling frequency by a factor ~18 significantly increases the compensation performance. Increasing the available data by adding a gaussian noise of 0.025°C and duplicating the data tenfold slightly increases performance as well but not to the same efficacy as higher temperature sampling.

4. Conclusion and Outlook

Data driven thermal error compensation can be a sustainable and effective approach for increasing the accuracy of MTs. The utilised ARX model achieves reduction of the volumetric error from 81 µm to 23.6 µm and sees significant improvement from the use of data augmentation to increase the sampling time.

Further work could reduce the amount of required measurements even further by utilizing simulations for pretraining compensation models or decreasing the required measurement time of the kinematic calibration cycle.

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