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

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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, as well as additional synthetic, data points available for training. The employed ARX model can reduce the volumetric error by around two thirds. The use of data augmentation represents an increase in volumetric modelling accuracy from 48.2% to 65.8 % without requiring any additional measurement effort.

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]. To enable compensation 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 a two model strategy to compensate fast acting effects on thermal errors of working space condition change in Swiss-type lathes. Also Infrared images can be used to compensate for the thermal expansion of a spindle using deep learning methods [8]. 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, where for example flips of images creates numerically very different data [9]. Oh et al. [10] 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 [11], which is especially important for thermal errors which are a continuous phenomenon with typically pronounced hysteresis effects [12].

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

2. Methods

Different data augmentation techniques and the experimentally investigated MT, as well as the utilised compensation architecture are described in this section.

2.1. Data augmentation for thermal compensation models

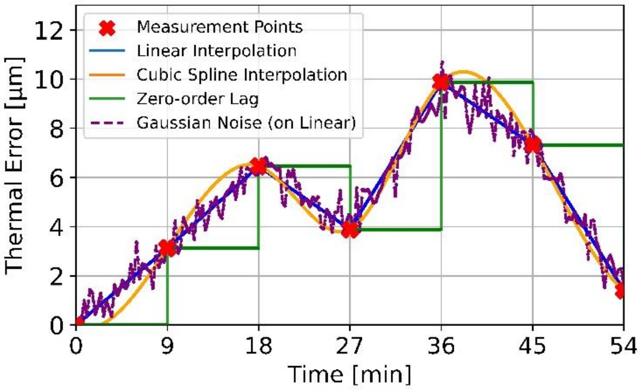

Figure 1. Visualization of the different interpolation strategies for 5 measurement points of a thermal error.

Figure 1 shows the augmentation approaches which were investigated for up-sampling the thermal error measurements: linear interpolation and cubic spline interpolation. A zero order hold of the thermal error is used for comparison. Furthermore, as a comparison original error sampling is applied, here the temperature data is analysed only at the original error measurements. This means that the model is trained and subsequently used at a significantly lower frequency, reducing the computational cost but also introducing a larger delay from thermal behaviour until the compensation can react. Additional data can be created by the addition of gaussian noise.

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 can be downsampled to different frequencies. 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. So original sampling (O.S) is every 9.16 min.

The measurement cycle measures measurement spheres placed on the clamping jaws of both turning spindles. The position of the sphere is measured using a touch trigger probe. The volumetric error is subsequently determined from the spindle centerpoint of C1.

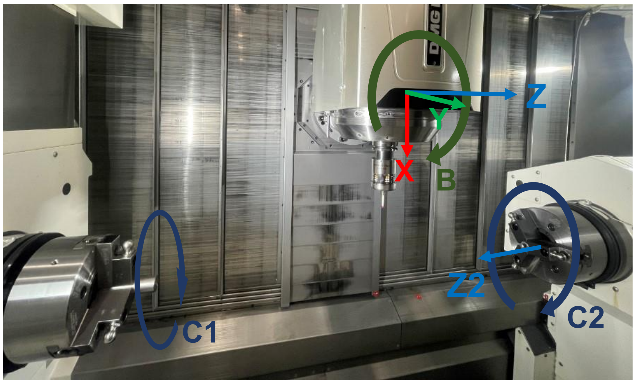

Figure 2. Kinematics of the NTX2000 with the used touch trigger probe and measurement artefacts mounted on the spindle jaws. The highlighted axes are the positioning axes of the MT.

2.3. Model setup

In order to generate a robust compensation model a time dependent ARX model is implemented for each zero point error in X, Y and Z. A correlation-based input selection ensures that good features are used in the model. Similar models were introduced by Zimmermann et al. [5] and Lang et al. [2].

3. Results

Figure 3 shows the volumetric error of tool to spindle 1 with and without compensation. The root mean square error (RMSE) of the uncompensated thermal error of 10.2 µm is reduced to 3.7 µm after compensation which corresponds to a maximum reduction of 65.8 % with linear interpolation and added Gaussian-Noise (G.N.).

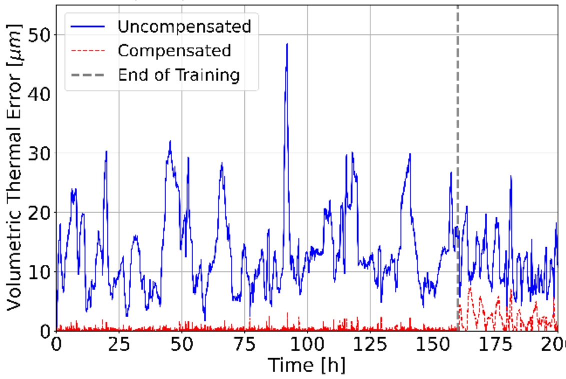

Figure 3. Volumetric thermal error of the tool to spindle 1 with linear sampling of the error.

	Linear		Cubic Spline		Zero Order Lag	
Δt [s]		With G.N.		With G.N.		With G.N.
2	64.1%	65.8%	63.9%	64.8%	41.3%	52.6%
10	61.2%	63.3%	63.0%	63.7%	33.7%	47.4%
30	60.3%	62.7%	62.2%	63.4%	35.2%	39.8%
60	59.3%	61.8%	61.4%	62.9%	14.2%	13.8%
	Original Data			Gaussian Noise (G.N.)		
O.S	48.2%			54.7%		

Table 1 Reduction of the volumetric RMSE on the validation data after model training. The original data (O.S) did not augment any data and sampled the temperature only once at the thermal error measurement.

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 and zero order lag performs the worst. Increasing the number of data points consistently increases the compensation performance. Increasing the available data by adding G.N. of 0.025°C and augmentation of the data fivefold increases performance as well in 12 out of 13 cases. This also ensures a faster model update on the machine and therefore a quicker reaction time of the model to sudden changes in the temperatures and behaviour of the MT.

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 a reduction of the volumetric error from 10.2 µm to 3.7 µm. Data augmentation by suitable interpolation of the slower measurements, as well as adding the same data with added gaussian noise showed consistent improvements of the model accuracy.

Further work could reduce the number 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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