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Application of the adaptive Monte Carlo method in a five-axis machine tool calibration uncertainty estimation including the thermal behavior☆

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ABSTRACT

Calibration of the geometry of five-axis machine tools needs to be performed periodically since the machine accuracy has a direct impact on machined parts. Because mechanical adjustment and a software correction may be done using calibration results, the measurement results must be evaluated. In this paper, the scale and master ball artefact (SAMBA) method is evaluated through the estimation of the uncertainty of the identified machine geometric error parameters. This approach has the multi-input multi-output (MIMO) model and an iterative solution that makes it challenging to apply commonly used uncertainty calculation methods The Guide to the Expression of Uncertainty in Measurement Supplement 2 (GUM S2) gives the opportunity to estimate the uncertainty of a MIMO model through the adaptive Monte Carlo method (MCM). In order to include all the uncertainty sources, the input uncertainty is estimated from the repeated calibration tests performed in different thermal conditions (with and without the warm-up cycle). The uncertainty is calculated for each of the identified machine geometric error parameters along with their covariance. The correlation between the output variables and the impact of the machine state, before and during the repeated calibration, are analyzed. The results demonstrate that the machine tool geometry variations occur even without the warm-up cycle performed before the calibration. Moreover, machine performance has an impact the calibration results.

1. Introduction

The calibration of a machine tool requires estimating the geometric errors parameters of its linear and angular axes. Schwenke et al. [1] described and classified different methods for machine tool calibration into two groups: direct and indirect methods. The former allow measuring the axis errors without the influence of the other axes and are commonly conducted using laser interferometry techniques [2,3]. The latter identify errors using different measuring devices, such as ball-bar [4], various 2- and 3-D artefacts [1,5–7], laser trackers [8] and laser tracer [9] or an uncalibrated artefact probing [10].

Once the estimates of the geometric errors parameters have been obtained, the decision of using them for a correction and/or compensation must be made. That is why the calibration results should be evaluated. One of the evaluation methods can be conducted through the predicted (with and without calibration) workpiece feature errors as Bringmann et al. proposed in [11], that allowed choosing the most optimal calibration method. The estimated calibration results can also be evaluated through their uncertainty as any other kind of measurement result. Since the measurement models used in the indirect methods are complex and are multi-input multi-output, the general uncertainty framework (GUF) for a single output presented in GUM [12] cannot be conducted.

Bringmann et al. [13] estimated the uncertainties on the machine geometric errors parameters of a three-axis machine tool obtained with the model-based indirect calibration method, called "chase the ball", using general Monte Carlo method (MCM). This approach requires adding noise to the geometric errors in the simulated machine model. The noise values are chosen arbitrarily from standards or machine specifications without considering correlations between them or the obtained calibration results. The authors also depicted that the machine performance (the positioning accuracy and repeatability) has a significant impact on the calibration results. Other researchers also applied MCM based on GUM Supplement 1 (GUM S1) [14]. Andolfatto et al. [15] used the adaptive MCM to estimate uncertainty on machine tool axis location errors with the confidence intervals. Schwenke et al. [16] estimated the uncertainty on six parametric errors of the Y-axis of a coordinate measuring machine (CMM) and on a milling machine. The machine errors are identified using a laser tracer. The displacement measurements noise is estimated as normally distributed random

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numbers without considering the correlation between the input data. All of the mentioned approaches use the MCM for a multi-output model but do not consider the full uncertainty structure (standard uncertainties and covariance of the measured data) (JCGM 104:2009 6) [17], nor the coverage factor associated with the number of the estimated parameters.

The method for generating the correlated measurement signal that can be propagated through the MCM was presented by van Dorp et al. [18]. The authors performed the short- (with high resolution) and long-wave (with lower resolution) direct calibration measurements of the geometric errors on the coordinate measuring machine (CMM). The registered signals were used to generate the surrogate signals using the auto-correlation algorithms so that the correlation between them was kept. The obtained measurement signals variations were propagated on the ring diameter measurement uncertainty.

Not only the correlation of the input quantity should be considered, but the correlation between the calibration results (machine geometric error parameters) should be estimated as well. Obtained correlation coefficents can be later used as one of the machine model optimization factors as it has been presented in [19]. The indirect calibration methods allow estimating many geometric errors simultaneously. That is why the covariance between them should also be considered when the uncertainties are calculated. Moreover, the coverage factor should be based not only on the desired coverage probability but on the number of the output values as well. The opportunity of calculating the uncertainty on the multi-output model results with the full uncertainty structure is given in GUM S2 [20]. It has been applied by Eichstadt et al. [21] to an efficient uncertainty estimation in a challenging case of a dynamic measurement, which requires simulating and processing a large amount of data The direct MCM uncertainty estimation results were compared with two other MCM memory-efficient approaches. Performing the data processing before application of MCM allowed the authors reducing the size of the generated samples and obtaining the uncertainty estimation results that were validated with the direct MCM.

In this paper, the machine geometric error parameters are identified using the SAMBA [10] method, whereby the volumetric observations are gathered using an uncalibrated artefact made of a number of spheres, a calibrated fixed length ball bar (scale bar) and a touch trigger probe mounted in the machine tool spindle. The machine, with its axis location and linear axis positioning error gains, is modeled using rigid body kinematics so that its geometric error parameters can be estimated. This method is based on a multi-output model – all the machine geometric errors are calculated simultaneously from the volumetric measurement indications (probing data). In this paper, since the SAMBA method is based on multistage and iterative calculations, analytical procedures are not easily conducted. Thus, the adaptive MCM [20] is followed. The GUM S2 provides guidance on the propagation of the uncertainties for a non-linear multi-input multi-output model. However, it does not describe how to estimate the uncertainty when an uncalibrated artefact is used, nor how to include the measurand changes in the uncertainty budget. The measurand changes were demonstrated to be a significant error source of the calibration results by Bringmann et al. [22]. Moreover, as it was depicted by Knapp [23] for a direct calibration method using laser interferometry, the calibration conditions impact the measurement result. The author pointed out that, in practice, the calibration is performed in a workshop, not in laboratory conditions, and the test uncertainty should not be propagated only from the measuring device uncertainty. The non-optimal conditions were amplified in the uncertainty propagation in order to demonstrate that uncertainty results, obtained for example, only from the laser interferometer displacement, may not reflect the reality of the calibration process.

Changes in the thermal conditions affect the geometry of the machine, which results in changes of the tool center point (TCP) displacement. This issue has been studied by Mayr et al. [24]. The authors demonstrated the necessity of including temperature changes for various axis positions so that they could be compensated with high accuracy in the whole volume of the machine tool. A similar issue was analyzed by Ibaraki et al. [25]. The authors used a tracking interferometer to identify the 2D geometric errors and measure the thermal effects on a 2D trajectory on a three-axis machine tool. Thermal effects were assessed by performing the measurements after one hour runs of a spindle at different speeds. This approach included thermal effects on a 2D plane and not only in few points as it is required during a standard thermal test. The uncertainty estimation of the estimated trajectories was performed similarly to the one presented in [11]. Thus, the identified geometric errors uncertainty is modeled with the values from the standard or defined by the supplier.

The approach for a multi-axis machine tool calibration including thermal effects on rotary axes occurring during the machining is presented in [26]. The proposed method identifies the machine geometric error parameters from the probing (on-the-machine) of the blank part and the machined parts. That way, changes occurring during the machining process are included. However, this approach makes the assumption that the linear axes have high positioning accuracy. The uncertainty of the calibration results is, again, based on the approach presented in [11] and [22]. Moreover, the authors point out that when the calibration is performed when the machine is in the cold state, the results do not reflect the machine normal operating conditions. Another method of including the thermal behavior of the machine tool has been presented in [27]. The authors have modeled the machine as a flat plate steel (or cast iron) structure and placed the temperature sensors on the machine components. The data gathered from the temperature measurement was used to map the temperature distribution and to calculate thermal deformation, which led to estimating the positioning error caused by that deformation. The calculated positioning error was compared with the telescopic double bar measurement results. That showed that proposed thermal model was able to predict over 60% of the thermally induced positioning errors. However, in this method, the machine geometric errors are considered constant in time.

In this paper, in order to include the measurand changes (geometric error parameters) and the calibration's thermal conditions, the uncertainties of the probing data are estimated from the repeated measurement conducted under different conditions (with and without the warm-up cycle). The warm-up cycle, performed before the measurement, allows simulating the machine's working conditions [28] and is required when the calibration (using direct methods) is following the ISO 230-2 standard [29]. However, the ASME B5.54 standard [30] (for direct methods) do not require a warm-up cycle, and the errors due to machine heat sources are not present prior to the tests [28]. Conducting the calibration series with and without the warm-up cycle allows demonstrating the machine performance variations and its influence on calibration results depending on the calibration pre-conditions. In the first case, without the warm-up cycle, the machine geometry variations are analyzed when the measuring conditions are not changing significantly. When the warm-up cycle is applied, the machine performance is studied when the temperature change is bigger. Despite the tests are performed in different thermal conditions, the applied geometric error parameters model does not include thermal errors and their changes. For all the measurements the same model is used to obtained the calibration results to depict the impact of the test performed with and without the warm-up.

2. SAMBA calibration method

2.1. Artefact probing

The SAMBA method allows estimating the machine geometric error parameters from the probing (using a touch probe mounted in the spindle) of a number of master balls (mounted on rods with different lengths) in different machine rotary axis indexations and a scale bar (probed at least once). The SAMBA artefact with the four master balls