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Evaluation of optimal positioning methods of integral deformation sensors for the correction of thermal errors in machine tools

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Abstract
Up to 75% of the overall workpiece error can be caused by the thermo-elastic behavior of the machine tool. Therefore, correction methods based on machine-integrated sensors were intensively researched in the last years, in order to determine the dislocation of the Tool Center Point (TCP) parallel to the process. One of these sensors is the integral deformation sensor (IDS), which detects the integral deformation along the length of a structural component of the machine. The integral deformation is the result of the directional temperature gradient along the length of the component. These measurements are fed into a mechanical model of each machine tool component to predict the deformation along the length of some significant outer surfaces, such as the guide ways on the component. Based on this information, the kinematic model of the machine tool can calculate the overall thermo-elastic TCP dislocation.
Before the installation of the IDS on the machine tool components, the optimization of the sensor arrangement is recommended, since it has a significant influence on the achievable TCP prediction accuracy. Several approaches to perform this step are known. This paper presents and compares an experienced-based approach and a mathematical optimization strategy. The arrangement of the IDS comprises the lengths and positions of the IDS within each machine tool component. The mechanical and the kinematic model using the IDS information are the basis for both the experienced-based and the mathematical approach. The first strategy is based on domain knowledge on the thermo-elastic behavior of the machine tool and on the interpretation of the IDS measurements. The mathematical strategy, on the other hand, changes the arrangement of the IDS on each machine tool component until the covariance with the overall TCP dislocation reaches its minimum.
Deformation, Measuring instrument, Optimization, Thermal error

1 Introduction

The integral deformation sensors (IDS) can provide a significant contribution to the determination of the thermo-elastic behavior of machine tools and subsequently the precision of the manufactured parts. A physical model, based on mechanical modeling and the kinematics of the machine tool, calculates the Tool Center Point (TCP) dislocation in real-time parallel to the machining process [1]. The determination of the optimal sensor placement can reduce the amount of sensors needed to reach the same prediction accuracy. It can also reduce the uncertainty propagation from the measurement uncertainty of the IDS data to the prediction of the TCP dislocation.

The application of optimal sensor placement techniques in practice is however bound to some challenges. Ideally, the optimal sensor placement is taken into consideration during the design and construction process of the machine tool. However, in case of a retrofit of the sensors on an existing machine tool, there are limitations with respect to the available installation space. The mathematical description of the allowable installation space has a direct impact on the computational effort that the optimization procedure will require. In practical terms, the installation space has to be discretized with a specific refinement, leading to a mesh with nodes indicating allowable positions of the sensors.

The arrangement of the IDS in this paper comprises the lengths and positions of the IDS within each machine tool component. This paper presents and compares two optimal sensor positioning methods in a simulation environment. On the one hand, an experience-based approach makes use of domain knowledge on the thermo-elastic behavior of the machine tool and on the interpretation of the IDS measurements. On the other hand, the mathematical optimization relies upon a general optimal experimental design criterion [3]. Every measurement contains measurement errors, which are often assumed to be independent and identically distributed. Under the assumption of a linear model, the true TCP lies inside the confidence ellipsoid around the computed (or expected) TCP. This method changes all sensor positions at the same time, until the longest axis of confidence ellipsoid of the predicted TCP dislocation reaches its minimum value.

The use case of this work is a 4-axis horizontal milling machine, as shown in Figure 1. The IDS will be placed at the column, the bed section underneath the column and the bed section underneath the table. There are practical limitations for the sensor placement due to piping, housings, measuring systems, drive elements and auxiliary systems. The figure below depicts the machine structure in grey, the ball screws in red, the guiding slides in blue, the guiding shoes in green and the measuring systems in orange.

2 Optimal Sensor Placement

The following sub-sections describe the working principles of the prediction and the optimal sensor positioning strategies. The main goal of the optimal sensor placement is to maximize prediction accuracy, while using the least number of IDS. Both the propagation of measurement uncertainty though the model and the model simplifications and assumptions of the model hinder the overall prediction accuracy.

From the standpoint of the prediction model using the IDS data to derive the TCP dislocation of the machine tool, the sensor placement is a set of parameters of the model. The accuracy of the prediction model depends also on its parameters. Hence, changing the sensor positioning and the corresponding parameters to the model should lead to changes on the overall prediction. The extent to which these parameters can change the outcome depends on the physical principles of the model used to interpret the behavior of the machine tool and the meaning of the IDS measurements.

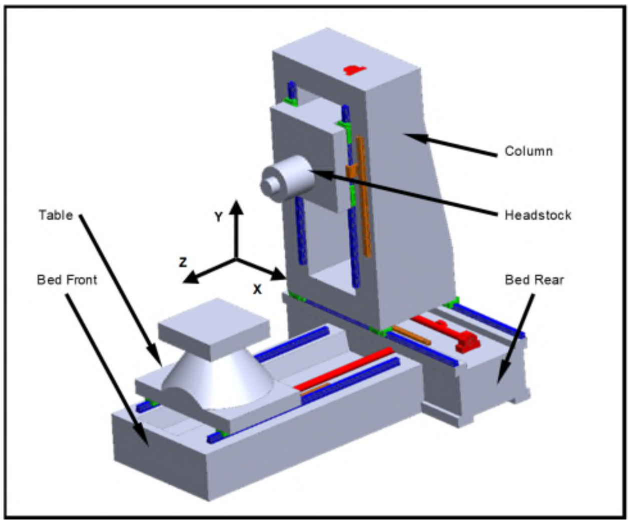

Figure 1. Demonstrator machine tool and areas of possible IDS placement

2.1 Prediction model and experience-based optimal positioning of IDS

The measuring principle of the IDS was explained in detail in [1], a brief summary is given in the following lines. An IDS measures the relative deformation of its two end points in one direction. When it is used for the detection of thermos-elastic behavior of machine tools, this measurement can be interpreted as the integral of the temperature distribution along its measuring length, multiplied by the specific heat expansion coefficient of the machine tool component. This leads to the resulting deformation distribution due to all thermal effects and heat transport phenomena that inflicted the machine tool component. The physical model that uses the IDS information contains two separate steps:

- the mechanical modelling of each machine tool component to calculate the overall deformation field of the component,
- the kinematic modelling of the entire machine tool to calculate the overall dislocation between tool and workpiece.

Both modeling steps influence the prediction accuracy. The overall chain of data and calculations from the collection of IDS data to the prediction of TCP dislocation is depicted in Figure 2. The model parameters for each modeling step are specific for the machine tool and do not depend on the thermal load.

The mechanical model follows the Euler-Bernoulli beam assumptions, which consider each machine tool component as a three-dimensional deformation and inclination field that can be described with one variable: the current position along the neutral fiber of the beam. The IDS are always parallel to the neutral fiber, so they measure only the longitudinal deformation of the machine tool component at their position. The distance of the IDS to the neutral fiber is a vital component to the interpretation of the IDS data: the farther away an IDS is from the neutral fiber, the larger the deformation this IDS is expected to detect.

The position of the IDS along the length of the beam is however a more complex parameter, because it includes the combinatorial consideration of all IDS on the machine tool component. The reason for this is that each IDS delivers a one-dimensional information, leading at first to a conclusion about the thermal expansion of the machine tool component. However, in order to detect bending modes with respect to one or two directions in space, another one or two IDS are necessary. Each bending mode would lead to one IDS getting elongated on the one side of the neutral fiber, while the other gets contracted. The presence of two bending modes on top of the thermal expansion would require three IDS in overall, for which the combination of expansion and / or contraction detected at each IDS can come from three different deformation modes: (1) thermal expansion; (2) bending around one transverse direction of the beam; (3) bending around another transverse direction of the beam.

On the other hand, the specific solution leading to the overall deformation field of a machine tool component depends also on the mechanical boundary conditions. A typical comparison to showcase this effect is the apparent difference of the resulting deformation between a fixed-free-end beam and a simply-supported beam. This information is also fed to the mechanical model, which in turn combines this information with the interpretation of the IDS data and tries to fit a polynomial equation of 2^{nd} or 3^{rd} degree to these known values of deformation at different points along the length of the neutral fiber. A 2^{nd} degree polynomial, for example, is solvable with three known values and leads to a quadratic deformation distribution.

It is thus evident how complicated it is to decide where to position the sensors on each machine tool component, in order to maximize the prediction accuracy of the TCP-dislocation. The higher the number of deformation modes, the more complex this deduction process becomes. This paper applies the optimal positioning methods based on the model calculations for up to three deformation modes, as described above.

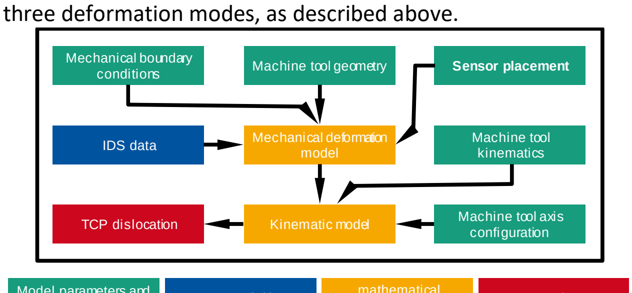

Figure 2. Overview of prediction model with model parameters, as well as input and output variables

It should be noted that additional deformation modes, that can be present in practice, such as torsion and shear strain, are not included. However, these deformation models are negligible in machine tool configurations such as the demonstrator machine tool used in this paper (Figure 1). Shear strain is negligible when one dimension is significantly longer than the other two, which is the case for all machine tool components considered for sensor placement. Torsion is not expected in such machine tool configurations, because it arises mostly on cross-beams, portals or horizontal headstocks.

The experience-based optimal positioning approach makes use of the information described above and combines them with analyses and experience gained about the thermo-elastic behavior of machine tools and their components.

2.2 Mathematical approach for the optimal positioning of IDS

The two approaches require different types of initial knowledge and different processes to find a set of optimal sensor positions, as can be seen in Figure 3. The mathematical model starts from the geometric and kinematic structure of the machine. The two main building blocks for the optimization are the optimization loop *sensor position -> svd -> sensor positions* and the *Bernoulli beam model*. These blocks lead to the optimal sensor positions. In contrast the experience based approach requires only the domain knowledge.

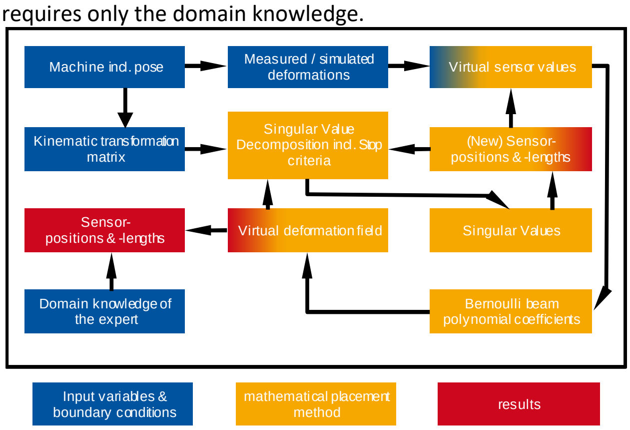

Figure 3. The model-based optimization approach

The mathematical model of the sensor measurement to machine displacement map can be written as

$$u(f) = A(x_c) \cdot B_c(x_s, l_s) \cdot (f + \theta) \quad (1)$$

where the coefficient matrices B_c and A represent a constant and a nonlinear local sensor model respectively and the coefficient matrix $A(x_c)$ maps the local displacements to the global space. Hence, the last coefficient depends only on the local orientation of the machine components, whereas the first two depend only on the sensor locations and configuration.

Furthermore the sensor measurements are not exact, but contain independent normally distributed measurement errors $\theta \sim$ N (0, σ^2 2I) with zero mean and standard deviation σ. Let us first neglect the nonlinear part B_n. Then the Jacobian J of the machine displacement u is then given by

$$J(x_c, l_s) = A(x_c) \cdot B_c(x_s, l_s) \quad (2)$$

Our aim are highly confidential computations of the machine distortion from the measured displacement. In other words, we wish to find sensor positions x_s and lengths l_s , such that the confidence ellipsoids are small. Due to the geometric nature, there are several choices [3]:

(i) One can minimize the length of longest axis. This corresponds to the largest singular value of the Jacobian matrix J.

(ii) One can minimize the volume of the ellipsoid. This corresponds to the product of the singular values of J.

We use the criterion (i) and look for the optimal sensor position and sensor lengths, such that the largest singular value becomes minimal. Furthermore, we constrain the sensor positions to their initial faces and orientation.

All optimization variables are continuous, but bounded by geometric constraints. As suitable numerical algorithm for these problem is the interior point method [5].

First, we start from an initial sensor placement, see for example Figure (4a). These initial sensor positions are symmetric in the centers of the surfaces and every surface contains exactly one sensor. This initial placement has the largest singular value around 2.7. After optimization, we obtain the placement in Figure (4b) with largest singular value around 1.3. In other words, the optimization halved the length of the longest confidence axis.

The basis for this optimization approach is a mathematical model of the sensors. Therefore the optimal sensor positions are only as good as the model describes the sensors and the machine kinematics and cannot correct any modelling error. In particular the optimization does not add any additional information, but increases the information from every sensor.

3 Results and comparison

In order to compare the experience-based with the mathematical approach, a probability distribution of random values will be used as a reference input value. The standard deviation of this distribution will be the measurement uncertainty of the IDS, which is known to be ±1 µm per meter IDS length from past experimental investigations [1]. The average value of the distribution will be zero, in order to evaluate the propagation of distributions with the so-called Monte-Carlo method [5]. The deformation model that predicts the TCP-dislocation will run twice for this input value: once with the sensor placement derived from the experience-based method and once with the sensor placement derived from the mathematical optimal positioning approach. The output values of each prediction run will be statistically evaluated.

A good sensor placement should not allow for an amplification of the scattering interval, nor a shift of the average value. The 95% confidence interval will quantify the scattering interval in this paper. The bigger such effects are present, the less trustworthy is the sensor placement and consequently the methods that derived it would be less effective. A shift of the average value indicates a non-linearity in the model calculation, which exists only in the kinematic model. In order to investigate the influence on the scattering interval, the model was linearized around the local deformation in the work-space of the test machine tool.

The mathematical optimization strategy leads to a significant reduction of the scattering interval on the prediction of the TCP dislocation as shown in Figure 4. Since the test machine tool is symmetrical with respect to the YZ-plane, the scattering along this direction is very low in both sensor placements and changes inconsiderably. The scattering in Y-direction is reduced to more than 50% and in Z-direction to almost 60%. This indicates a higher repeatability for the model prediction, which means that the overall prediction uncertainty is improved. Based on the fact that the optimization run lasted only a few minutes, the application of this method in practice can be beneficial. The Monte-Carlo simulation that allows the evaluation of the results also lasts only a few minutes.

4 Summary and Outlook

A comparison of the strategies in this paper leads to the conclusion that the mathematical optimization can provide useful results with reasonable numerical effort. The optimization for one kinematic pose lasts only a few seconds. The reason for this is that the physical model that the mathematical optimization is built upon is a non-linear algebraic equation system. Since the model consists solely of algebraic equations, the Jacobian (2) is given explicitly. Therefore the singular values are available from standard numerical software. The results in Fig. 4 clearly indicate a significant optimization of the prediction of the TCP dislocation. As described in Ch. 3, the results of the optimization can be interpreted with the domain knowledge of the experts. More specifically, the results lead to conclusions about the mechanical behavior due to the mechanical boundary conditions and/or the relevance of deformation modes of each machine tool component due to the machine tool kinematics. These conclusions can only be drawn by such mathematical approaches.

Nevertheless, it must be noted that the mathematical strategy requires an initial sensor placement, which can only be deduced based on domain knowledge. Hence, this approach cannot replace the domain knowledge of the experts competely. A sensitivity analysis of the initial sensor placement has to be studied in the future. Another drawback of the mathematical method in this paper is that it does not optimize the sensor placement for all kinematic poses of the machine tool axes simultaneously. Instead, the authors ran an optimization of the sensor placement for the combination of three positions for each machine tool axis (the combination of 3 positions for each of the three axes leads to 10^3 = 1.000 combinations) separately.

Also, experimental data with the optimal sensor placement must be gathered and compared with the experience-based sensor placement, in order to validate the effectiveness of the mathematical optimization strategy in an industrially relevant environment.

The methods proposed in this paper were focused on parallel configurations of the IDS, which means that all IDS on a machine tool component are parallel to each other and to the axis of the longest dimension of the machine tool component (beam neutral fiber). There is no validated interpretation model yet of IDS being arranged with an inclination to each other or to the neutral fiber of the machine tool component. The mathematical optimization method presented in this paper calculates analytically the covariance of the predicted TCP dislocation based on the model equations, which classified this method as a so-called "white-box" strategy.

A "black-box" strategy, on the other hand, which is based on measurements of the IDS and the real TCP dislocation instead, will be also evaluated in the future. However, such a strategy is bound to higher installation and optimization effort, since a higher amount of pre-defined, possible optimal IDS positions have to be installed on the machine tool of interest. Then, experiments will have to be designed, in order to measure the real TCP dislocation while applying test thermal loads on the machine tool. Such strategies are limited by the fact that the test thermal loads are not the same as the real loads on the machine tool under operating conditions and by the pre-defined IDS positions.

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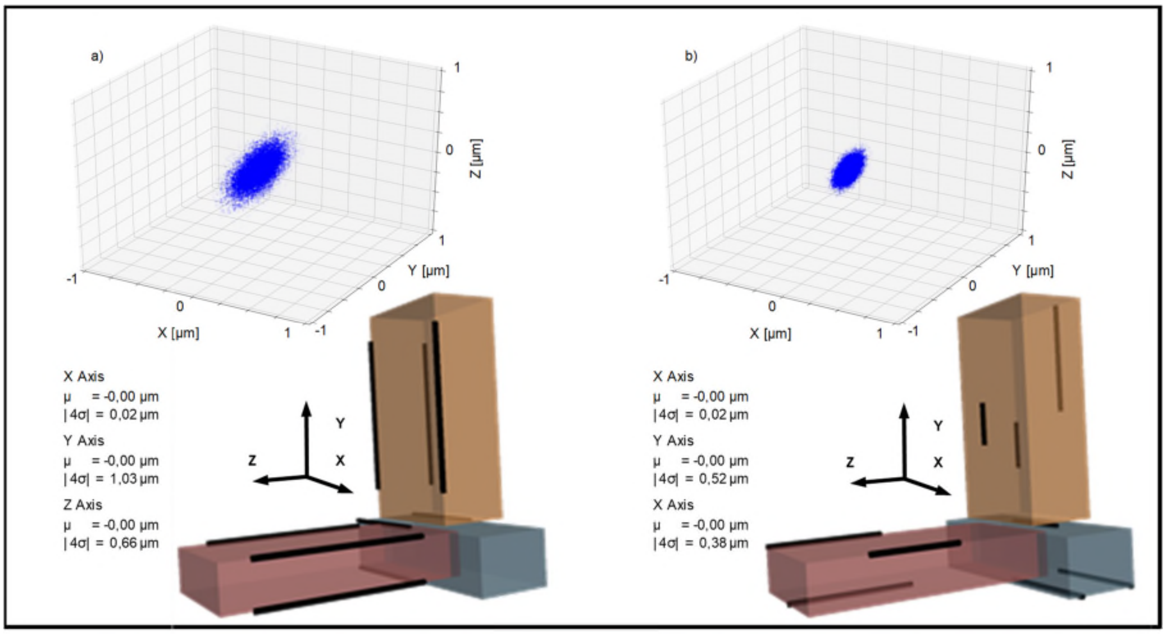

Figure 4. Sensor placement a) based on the experience-based method and b) based on the mathematical method. Prediction of the TCP-dislocation for a measurement uncertainty of **±1µm** per meter IDS length c) based on the experience-based method and d) based on the mathematical method