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Quality Control Loop for Tool Wear Compensation in Milling Process using different Optimization Methods

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Abstract

Milling is one of the most important cutting processes in the manufacturing industry. Accordingly, optimization measures in this area have a great influence on the efficiency in modern production systems, which in many cases is composed of entire machine parks consisting of milling machines. Tool wear on milling machines reduces tool life and causes quality features of manufactured products to drift out of the target range. Currently, this is associated with a high effort to detect and control occurring deviations. In the following, an approach will be presented in which the design of an automated quality control loop for milling processes based on the geometric detection of the manufactured components is developed. The subject is formulated as a mathematical optimization problem, which is solved using evolutionary algorithms.

Keywords: Closed Loop Quality Control, Milling, Optimization Algorithm, Evolutionary Algorithm

1. Introduction

From a production engineering perspective, the creation of products is always about meeting requirements [1]. With continuously increasing product complexity at the same time, systems that are responsible for the extent to which these requirements are met are moving into ever smaller tolerance fields. To keep up with this development, machines used are also being further developed and optimized in terms of process capability [2, 3].

In this context, cutting machine tools, as the basis for the production of all other capital goods, are of particular importance. The operation of such systems is associated with high investment and operating costs and is only worthwhile if maximum utilization of the technical availability is aimed for and downtimes are minimized as far as possible [4, 5].

One common source of quality inefficiencies regarding milling processes is tool wear [6]:

Tool wear during milling causes deviations between real and virtual tool geometry, resulting in a shift of manufactured features towards tolerance borders (as visualized in Figure 1) [7]. The goal is to align real and virtual tool geometry, which can be done by manipulating tool geometrical characteristics in the tool database.

These correction values are currently calculated in a manual process by measurement technicians in a trade-off between effort and scrap. An automated solution could improve the detection efficiency and measure the tool wear without interfering the manufacturing process.

This study aims to develop a quality control loop based on the evaluation of the geometric measurement of manufactured parts. For this purpose, the context is formulated as a mathematical optimization problem, which is solved with the use of an Evolutionary Algorithm and the Nelder-Mead Simplex Algorithm. Part of this study is an additional performance evaluation of the named algorithms.

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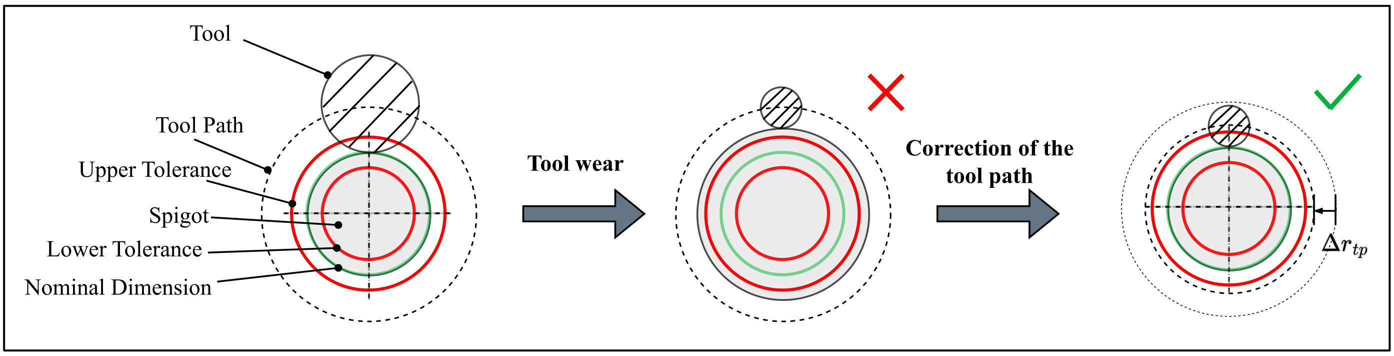

Figure 1: Effect of tool wear on geometric deviation of manufactured parts

2. State of the Art

Existing research focuses on determining the degree of wear of the tools used by observing the tool as well as the process data. However, the prediction of the wear rate and the associated geometric decrease is key for a wear correction.

Consequently, previous work will be investigated in the further course. These will be divided into the following groups depending on the process type (direct or indirect process) and the monitoring form (intermittent or continuous): geometric measurement, control-integrated process monitoring and external sensor technology

2.1. Geometric Measurement of Tool Wear

Geometric measurement focuses on the direct determination of the geometric deviation of the tool from the standard geometry. As the most direct way to quantify tool wear, there are various internal and external possibilities for this. These include various mechanical tactile measuring methods as well as optical laser measuring systems. [8]. An example for such an approach is given by Zhang and Zhang [9], Dutta et al. [10] and Ong et al. [11]

2.2. Control-integrated Process Monitoring

In fully control-integrated monitoring systems, the wear condition is monitored via the data recorded internally in the machine, such as torque or current signals. Using suitable methods of signal analysis and data extraction, mathematical wear characteristics can be determined on this basis. The biggest advantage of this type of monitoring is the elimination of difficult-to-implement external sensors and additional hardware. A high-quality input signal is a crucial prerequisite for making accurate statements. Most research approaches focus on the detection of tool failures by detecting special events and the exceeding of defined process change limits [12]. The goal is to immediately shut down all drives in the event of a breakage in order to prevent further, potentially very costly damage to the machine. Here, as with the use of external sensors, the focus is on clever information extraction from the raw data [8].

Related approaches were developed by Renones *et al.* [13], Zhang [14] and Xu *et al.* [15].

For further work in this context, the reader is referred to Mohanraj *et al.* [12].

2.3. Usage of external Sensors

Like control-integrated process monitoring, the use of external sensor technology requires an intelligent process of data analysis and feature extraction downstream of the data acquisition. The big difference is that a signal specifically dedicated to wear is acquired in a targeted manner in order to be able to make better statements about the wear behavior of the tool in a simpler way. However, this requires additional external sensor technology to be integrated into the process, inflicting additional cost. Because of the complex motion kinematics, design measures for this are correspondingly difficult [8].

Most condition monitoring approaches concentrate on the detection of vibration and structure-borne noise signals and the recording of cutting force curves, since these signals show the greatest correlation with advancing wear [12]. Information about the exact state of wear can be obtained by means of analyses in the time domain (mean, min, max, median of the signal) or in the frequency domain, e.g. in the form of a Fast Fourier Transformation. With the technique of sensor fusion, different sensor signals can be considered united for optimized information extraction [12]. Representative works for the previously mentioned three different types of signals were presented by Liu and Liang [16], Balazinski *et al.* [17] and Alonso and Salgado [18].

2.4. Research Gap

In summary, the current state of the art is characterized by the tension between intermittent approaches with high accuracy and continuous wear characterization approaches with low predictive accuracy. The following studies aim to resolve this tension with the help of a novel approach which is capable of accurate correction statements and waives process interruptions.

3. Methodology of Milling Process Deviation Correction

There are various tools in the milling environment (ball nose end mills, drum end mills, T-mills, angle end mills, etc.) whose holistic coverage in this context would be too complex for the first step. For this reason, the approach will initially focus on the correction of the most commonly used cylindric end mills. In addition, features with complex mathematical tool interrelationships exist. These exceptional cases are also not to be tackled for the time being. Accordingly, the methodology developed focuses on the correction of simple geometric distance features.

The rough procedure is shown in Figure 2. The measurement of the manufactured part geometry shall serve as the basis of the calculation. The correction algorithm shall then compute the optimal correction values via a comparison with the nominal geometry, which is specified in an initialization file. In order to be able to formulate the optimization problem, a cost function is needed to describe the correlation of the quality characteristics with the tool correction values. In addition, this cost function must be able to take tool couplings into account. To explain this in more detail a simple constellation is considered:

A cuboid has two distance features defined as perpendiculars between the respective opposite planes. Feature 1 depends on plane 1 and plane 3. Feature 2 depends on plane 2 and plane 4. Now, planes 1 and 2 are manufactured by the main cutting edge (i.e. the circumference) of the same tool (WKZ 1). In this example, planes 3 and 4 are to be produced by two different tools (WKZ 2 and WKZ 3) Now both feature 1 and feature 2 depend on tool 1. A change of the compensation value of this tool influences both features. In the same way, when the correction values of the other tools are varied via the dependency on the coupled tools, all of them are automatically coupled with each other. The cost function, which is modeled below as an RMS value, must therefore be able to take this into account.

The correction algorithm aims to describe the influence of a geometrical tool correction value on all associated features as a mathematical optimization problem. The minimization of these is to produce correction values for the respective tool parameters which guarantee the optimum dimensional accuracy of the subsequently manufactured components. After the correction, each feature should therefore have a minimum difference to its tolerance center, which is defined as the control value at this point. Therefore, two pieces of information are required for this: The actual state of the features gathered through the measurement report, as well as information on the target state of the component geometry. This information is essential to assign a tool to each feature and to define how the correction of the tool is incorporated in the design of the respective feature.

In the following, first a correction equation will be derived, which describes the influence of the correction of a tool on a feature and from which finally the optimization function will be built. Based on this, a second correction equation is developed, which takes into account the coupling of tool correction values by coupling features. These build the fundament for the subsequent development of the optimization function

3.1. Correction equations for independent features

The correction equations have the task of describing how the correction of a particular tool affects the features it produces. Since end mills remove material both with the face and with the circumference, and therefore can wear both in length and circumference, in principle two cases must be covered - length and radius correction. In addition, it must be taken into account that the offset of the tool path, depending on the design definition of the feature, can enter into a dimension differently. The result of this investigation is the first equation, which describes the correlation between a correction value of a tool and it's depending one-dimensional feature:

$$F_{n+1} = F_n - \frac{CV}{k \cdot s} \tag{1}$$

- F_n: Last measured value of the feature
- CV: Correction value of the tool dimension (length or radius)
- k: Contour parameter
  - inner = 1, outer = -1
- s: Symmetry factor,
  - asymmetric s = 1, symmetric s = ½

The equation is built up from the following components:

F_n is the last recorded value of the feature, but can also be an average of the last measured values. The correction value of the tool, depending on the constructive definition of the feature, is subtracted from this. This constructive definition is described by two parameters: The contour factor k describes whether the wear of the tool, i.e. the decrease of the length or the radius, is included negatively or positively in the feature. The symmetry factor s doubles the effect of the

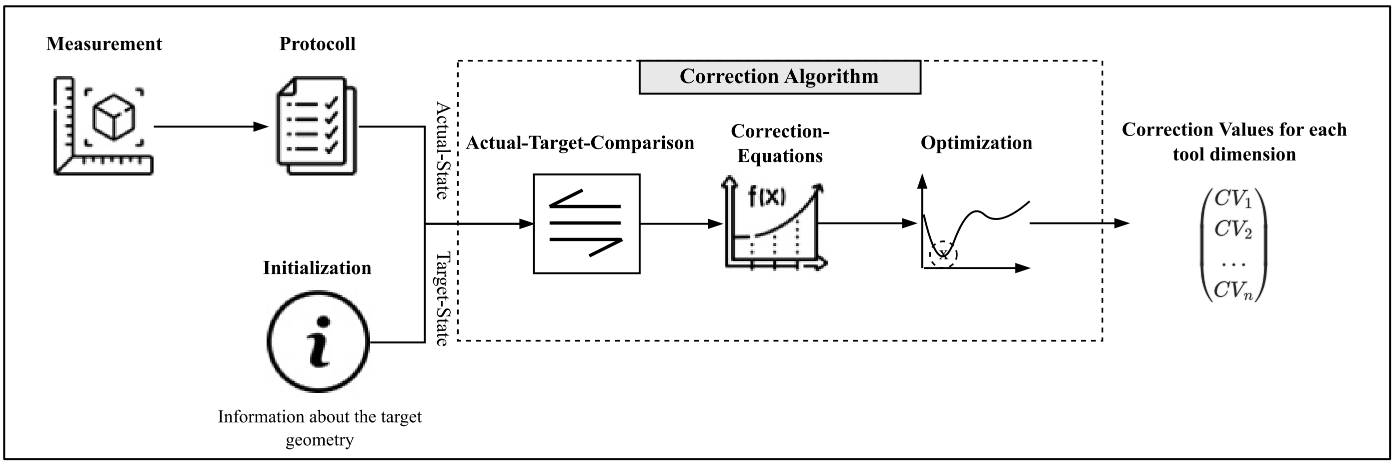

Figure 2: Workflow of the Correction Process of Measurement based Deviation Correction

compensation value for features where a tool enters both definition planes.

With these considerations the described Equation (1) is able to predict feature values of non-coupled, simple distance features after introducing a certain tool correction (in length or radius).

3.2. Correction Equation for coupled Features

Now Equation (1) just describes one-dimensional features. In this context these are features, which only depend on one tool parameter and is created by either the primary cutting edge (circumference) or secondary cutting edge (length) of the end mill. However, as explained previously, another equation is needed that is capable of describing coupled quality characteristics - that is, features into which two tool parameters enter. Figure 3 is showing examples for such features. As seen in the Figure, coupled features depend

$$F_{n+1} = F_n - k_1 \cdot CV_1 - k_1 \cdot CV_2 \qquad (2)$$

on 2 involved tool parameters. In the example, the two features depend respectively on the radii or the lengths of the end mills. Of course, mixed forms can occur.

- F_n: Last measured value of the feature
- CV_1: Correction value of tool parameter 1
- CV_2: Correction value of tool parameter 2
- k_1: Contour parameter of tool 1
- k_2: Contour parameter of tool 2

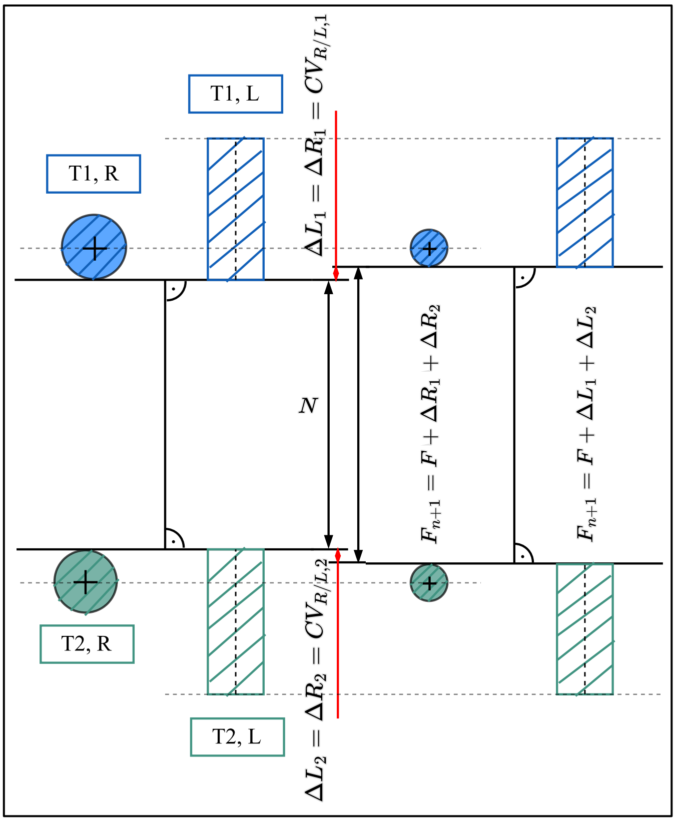

Figure 3: Coupled Features depending on 2 tool parameters involved in their creation

In the superordinate context, this results in a coupling of all features dependent on This will be explained in the next step in more detail.

3.3. Development of the Cost Function

The biggest challenge in the implementation of coupled features is the construction of the optimization function. This represents the relationship between correction values and the resulting geometry. Only in the context of coupling features, these can become significantly more complex. The reason for this is that each coupled feature links two tool parameters. If another coupling of an already coupled tool parameter is caused in another feature, the dimension of the error function increases by one.

In order to be able to formulate the situation as a mathematical optimization problem, equations (1) and (2) must be considered in a suitable context. The mean square error (MSE) is a suitable distance measure for this purpose:

The distance considered here is the difference between the

$$MSE = \sum_{i=1}^{n} \left(\frac{F_{i+1}(CV_i)}{w_{tol,i}} \right)^2 + \sum_{i=1}^{m} \left(\frac{F_{i+1}(CV_{i,1}, CV_{i,2})}{w_{tol,i}} \right)^2 \qquad (3)$$

corrected feature prediction and the control value R (middle of tolerance field). Via the residual sum of all associated uncoupled and coupled features of one correction path containing all associated features, the described relationship concretizes to:

- $w_{tol,i}$: Width of the tolerance field of the certain feature
- $First\ sum$: for uncoupled features
- $Second\ sum$: for coupled features, depending on 2 correction values

The minimization of this sum results in the optimal correction values for the involved tool parameters. Features with larger deviations are more strongly included in the correction value calculation due to the quadratic nature of the error function. Problematic constellations could arise when different features have different tolerance field widths and the permissible deviations are in different dimensions. by dividing the individual terms by the respective width of the tolerance field, this problem can be circumvented completely

3.4. Optimization Algorithms

For multidimensional optimization, an Evolutionary Algorithm (EA) for determining the optimum is developed and contrasted with a Simplex Algorithm. The goal is to evaluate the performance of an Evolutionary Algorithm in this context beyond the application in this example.

In an initial parameter study, the following hyperparameters ranges of the algorithm were defined:

- Pool size = [50; 200]
- Fitness function = MSE (equation (3))
- Recombination parameter = [0.5; 0.9]
- Mutation Parameter = [0.001; 0.005]

After determining optimal hyperparameters, the EA with the appropriate parameter combination is contrasted with the

Nelder-Mead Simplex Algorithm, which can be used to solve non-linear optimization problems.

3.5. Validation

For validation a part is designed which is manufactured by 4 different milling tools to be able to build multi-dimensional coupling paths. The goal is to simulate a certain complexity in which the correction algorithm and the used optimization algorithms are challenged. The procedure is visualized in Figure 4 and is defined as follows:

After an initial calibration of the manufacturing process, the tool parameters are manipulated by previously defined offset values, as already described. The aim is to calculate exactly this offset from the measurement of the manufactured product via the correction algorithm. The measurement is performed by a CMM in the next step. The resulting measurement protocol is the calculation basis for the correction value calculation by means of correction software, which must be initialized beforehand for the manufactured component. The calculated correction values are then compared with the introduced offset. Independently of this, the calculated correction values are transferred to the system and it is checked whether the dimensional accuracy is improved.

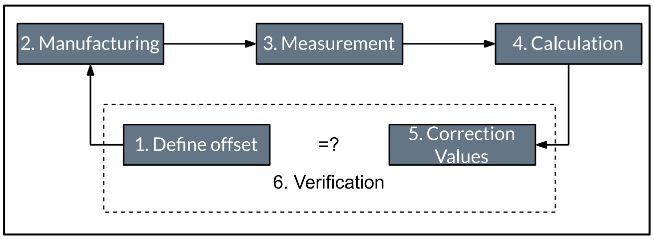

Figure 4: Validation Process

4. Results

At first the used optimization algorithms are evaluated. After this, the validation of the correction algorithm itself is done based on the results of the more performant algorithm.

4.1. Validation of the Correction Algorithm

A total of 10 control trials were conducted to validate the approach. In order not to go beyond the scope of this article, the procedure will be explained in more detail on the basis of one test. After an initial calibration, the geometry parameters of the individual tools are manipulated by the following offset values:

Table 1: Offset values for validation process

Tool	CV_L	CV_R
1	-0.1mm	0.1mm
2	0.13mm	-0.11mm
3	0.21mm	0.12mm
4	-0.012mm	-0.1mm

This offset is used to manufacture a part and then measure it using a coordinate measuring machine. The resulting geometric characteristics of the manufactured part can be seen in column 3 of Figure 5.

Based on its measurement protocol and taking into account the design specifications of the features from the initialization, the following correction values are calculated by the algorithm:

Table 2: Calculated correction values from correction algorithm

Tool	CV_L	CV_R
1	0.093 mm	-0.099mm
2	-0.131mm	0.107 mm
3	-0.216 mm	-0.121mm
4	0.115 mm	0.1mm

If the calculated correction values are compared to the introduced offset, it can be seen that the correction algorithm is able to calculate deviations between real geometry and virtual geometry on the basis of the measurement of the manufactured products. In this way, a minimization of the geometric deviation could be determined for all further tests after the calculated correction values were applied.

For getting a better grasp on the algorithm performance the results of one correction loop are demonstrated in Figure 5. It is clearly evident that the deviations can be reduced to a minimum. Of course, these cannot be completely zeroed out due to local force peptides, lubrication conditions as well as stochastic influences. In this way, the logic of the algorithm could be validated in all further tests.

Feature	Nominal value [mm]	Deviation before correction [µm]	Deviation after correction [µm]
D Zyl. Mitte 9	9	+207	+0
D Halbkugel 8	8	-211	-6
Distanz X 39	39	+219	-1
Distanz X 5	5	+19	-5
Distanz X 48	48	+240	-4
Distanz X 43	43	+220	+2
Distanz Y 5	5	+24	-8
Distanz Y 33	33	-15	-9
Distanz Y 48	48	+245	-2
Distanz Y 37	37	-1	-1
Distanz Y 8	8	-190	+8
Distanz Z 15 1	15	-21	+3
Distanz Z 15 2	15	-331	+2
DistanzZ 15 4	15	-21	+5
Distanz Z 7	7	-236	-6
Distanz Z 8	8	-256	-7
Distanz Z 5	5	-24	+2

Figure 5: Geometric deviation before and after correction with calculated correction values

4.2. Performance Evaluation of the Optimization Algorithms

The statistical experiment shows that even the best parameter combinations of the EA only converge to the solution calculated by the simplex algorithm, with non-negligible scatter at the same time. If we also compare the number of evaluations as well as the runtime, which is required on average in the case of the best solution combination of the EA, it becomes apparent that the evolutionary algorithm works significantly less efficiently in the case of this quadratic optimization function. While the simplex algorithm reaches the goal with only 378 function evaluations and 0.031s, the EA needs on average almost a factor of 50 more evaluations and 20 times the runtime.

Overall, it turns out for this use case that an EA for the optimization of quadratic, multidimensional functions is significantly less suitable than the simplex algorithm of Nelder and Mead as a deterministic method. Due to the limited scope of this paper, the exact comparison of the algorithms will not be discussed in detail.

5. Conclusion and Outlook

This work aims to develop a closed quality control loop for tool wear correction in milling application considering the geometric deviation of manufactured parts. The considered correlation is formulated as a mathematical optimization problem, which is described with a mean square error consisting of feature deviation terms. These error terms express the tool geometry-dependent deviation from the nominal value of the respective feature, which should approach zero through the optimal correction value.

Since there are various tool types with different geometric correction possibilities as well as complex features with dependencies on the tool parameters that are difficult to describe, this approach is limited to the consideration of features in the creation of which one or two tools are involved. The latter ensure that tool couplings occur, which result in a dimensional increase of the optimization equation.

After derivation of the correction formulas for one-dimensional as well as two-dimensional dependent features, in which the correction values of the involved tools depending on their definition are differently included, an approach for the construction of the optimization functions is developed. It considers coupling paths in which all features of the respective coupled tool parameters must be considered in an MSE optimization function. For coupled features, the correction of one tool parameter has an influence on the feature and thus also an influence on the correction factor of the other tool.

The validation is carried out in a real production scenario where a part is manufactured in which the tool geometry values have been deliberately adjusted beforehand. On the basis of the geometry values measured on a CMM, it could be proven that the algorithm is able to calculate tool correction values that minimize the manufacturing deviations of the next part to be manufactured.

Additionally, the investigations show new possibilities for the extension of the correction software and for the correction of component geometries in the manufacturing process. Current weaknesses are the rigidity of the software due the limitation to end mills as well as simple geometrical features. Extension to other milling tools and more accurate analysis of correctable features offer great potential.

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