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Simulation based process monitoring for single item production without machine external sensors

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Abstract

Process monitoring makes an essential contribution to process safety and workpiece quality in cutting machining processes. Conventional monitoring techniques have been successfully used to detect deviations from fault free production. In series production these techniques rely on a teach-in of confidence limits from identical previous machining. However, they fail in the context of small series or single item production since previous process data are hardly available. Therefore, an innovative "teach-free" monitoring strategy is required. In this work, a machine-integrated monitoring technique based on simulation is proposed, allowing monitoring of complete processes in single item production consisting of turning, milling and drilling.

1. Introduction

Process monitoring has become an important part of industrial production representing a valuable contribution to workpiece quality and process safety. Machining processes have become increasingly complex involving complex shapes as well as various materials and process types. Another aspect to consider is the introduction of modern turn-mill machining centers enabling six-sided machining. Moreover, the degree of automation has significantly

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increased. Therefore, in order to ensure and further increase productivity automatic error detection is of utmost importance. This work is meant to propose a new way to monitor machining processes from the very first workpiece based on the NC-code. The efficiency and applicability of the approach will be outlined in the following sections. The focus of this work is the derivation of reliable confidence limits from simulation data.

Conventional monitoring approaches in series production make use of sensor data of identical previous processes in order to generate a monitoring reference from which confidence limits can be derived [1]. These limits denote thresholds for specified sensor signals which may not be exceeded by fault free processes. There are several different process variables which reflect the actual state of the material removal process as wells as the tool state. These include cutting forces, noise, acoustic emission, vibrations, etc. Signals most suitable to give insight into the actual process and therefore chosen to be used for monitoring are measured by corresponding sensors. Measured signals are then processed by analogue or digital methods such as e.g. filtering in order to extract signal features that correlate to certain process states and can thus be used to identify process errors. There are several different techniques used for data-preparation and data processing of the measurement signals as well as different models and decision making strategies. A comprehensive survey of the latest developments is presented in [1].

A natural choice of a measurable quantity to be monitored in machine tools is process force providing very accurate and direct information about process errors. Most machine tools however do not dispose of internal force measuring sensors. It is worth mentioning that an integration of external sensors can be advantageous with respect to bandwidth and sampling frequency. However, the goal of this work is to rely purely on machine internal sensors for cost effectiveness. Process forces can be reconstructed on the basis of machine internal data [2], [3]. They correlate nicely to process forces and are therefore used as measured quantities fed to the monitoring system. Process signals have been reconstructed by machine internal signals before in order to be used for monitoring [4]. If the spindle current alone is not sufficient the approach can additionally resort to axis currents as well. State of the art approaches known from series production however fail in the context of small scale or single item production as reference data from previous processes is hardly available or cannot be generated economically [5]. Nevertheless, individualized single item production has become increasingly important and represents a considerable portion of industrial machining. It is therefore the aim of this work to derive an innovative new monitoring technique which does not require teach-in from machining first workpieces. Previous work on this topic has been done in [6]. A natural choice to replace teach-in by reference data is to use information from a process simulation. I.e. cutting parameters are to be derived from the NC Code. The Virtual Machine, provided by the cooperation partner INDEX GmbH, is a simulation tool mapping the machining process from the NC code at very high precision and returning the axis positions of the machine tool which are approached during production.
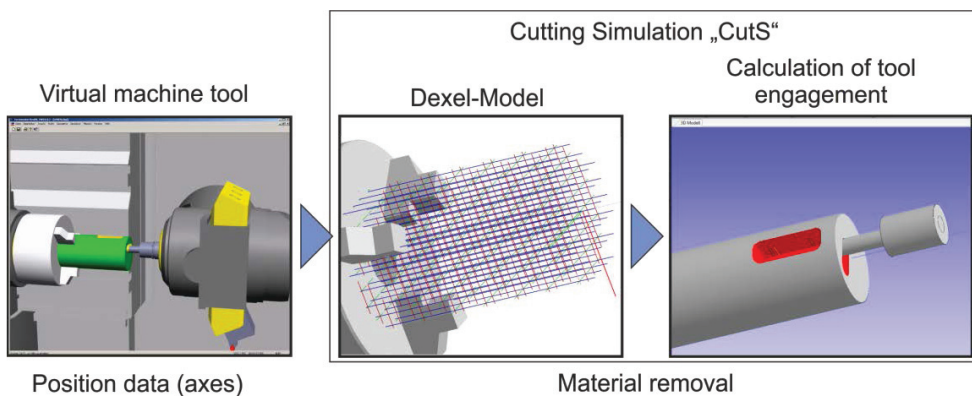
Fig. 1. Visualisation of simulation process (Virtual Machine and CutS). The Virtual machine generates axes position data on base of the NC Code, CutS provides simulation data such as the rate of material removal.

These data enable the derivation of cutting parameters via cutting simulation. At the Institute for Production Engineering and Machine Tools (IFW) a cutting simulation tool (CutS) was developed which is excellently suitable for this task [7]. Thus, after two simulation steps process quantities can be calculated from the simulated axis positions. In cylindrical turning processes for example the rate of material removal, contact lengths, the depth of cut and the width of cut correlate nicely to the measured spindle current. These quantities are simulated in CutS. They serve as a basis for the monitoring strategy without teach-in and are used to derive confidence intervals for machine internal signals. Process- and cutting simulation take place during work preparation and therefore do not require additional machine operating time, which is a considerable advantage in comparison to conventional systems.

The choice of suitable monitoring quantities (e.g. spindle- or axis currents) is made depending on the actual process type. Equivalent elementary parts of the complete process are assigned to specific groups (segments) already during work preparation, see section 2.1. A simple linear model can be used to estimate a respective signal based on different simulated covariables segment-specifically. The estimation is made with the help of online multilinear regression. Subsequently confidence limits can be derived by means of statistics and extrapolation of future values.

2. Approach

2.1. Segmentation

It is obvious that only process steps corresponding to an actual machining process will follow the specifically chosen linear model. It therefore has to be guaranteed that only these steps are taken into account for parameterization. Phases without tool engagement as well as acceleration periods exhibit different dynamical behavior. Parameterizing the model for a specific type of machining, these phases have to be strictly excluded. For this purpose the complete process is segmented during work preparation on basis of simulation and thus before actual machining. More precisely it is divided into a sequence of sub processes separated by phases without tool engagement.

A first step consists in analyzing periods of tool engagement. These periods are identified by means of a non-zero rate of material removal. This quantity is provided by the CutS cutting simulation tool. After that each elementary sub process has to be categorized according to the respective type of machining operation (cylindrical turning, face turning, face milling, drilling, etc.). These categories are referred to as segments.
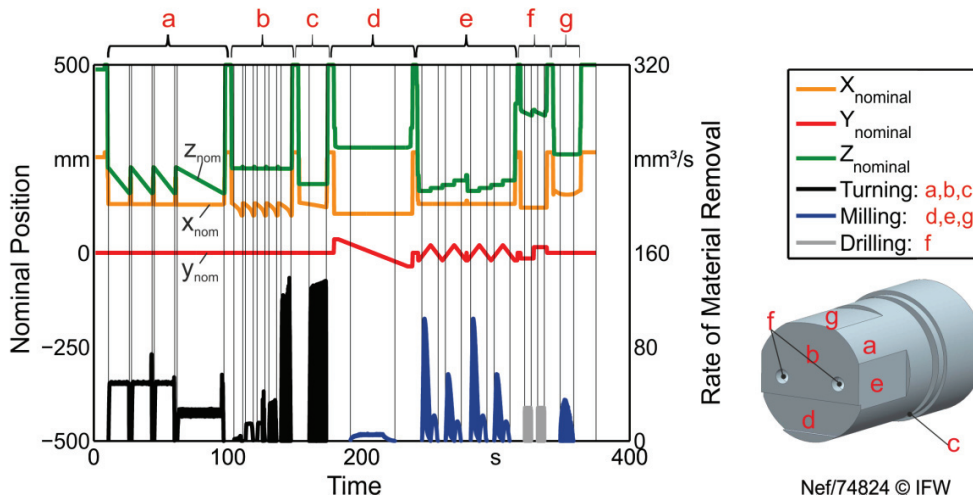

Fig. 2. Segmentation of a complete machining process. In a first step the process is divided into elementary sub processes which are subsequently classified and attributed a specific segment.

Every elementary process is part of a specific segment. In order to do so, elementary processes are classified by means of a tool identifier supplied by the INDEX-Virtual Machine on the one hand and an analysis of the set course of axis positions during the detected sub processes on the other hand (See Fig. 2). The division corresponds to the second sublevel of cutting processes defined by DIN 8589 (i.e. turning for example is divided into cylindrical turning, face turning, etc.). It is important to point out that further subdivision with respect to e.g. specific ranges of cutting parameters would lead to a potentially limitless number of different segments and thus different required monitoring strategies and is therefore refrained from.

A finer distinction does not seem to be necessary as the powerful approach of an adaptive multilinear monitoring model presented in the following covers differences in cutting parameters as well as different materials or machine tools as is demonstrated in section 3. In which extend it may yet prove useful is subject to further research. The presented segmentation concept was developed in close cooperation with Artis GmbH.

2.2. Synchronization

In this work segmentation of machining processes relies completely on simulation data. While this concept is efficient as no additional machine operating time is required its success depends decisively on the quality of synchronization between identified elementary processes and measured data during machining. In this work a position- based approach was chosen, i.e. synchronization is carried out with respect to position data rather than actual time steps. More specifically it is carried out on the basis of the different position components of the tool center point (TCP) which are simulated during process planning on the one hand and which are recorded during machining on the other hand. A simple, yet powerful approach is used to align both time series. For any measured set of coordinates, the corresponding simulation data set is found by looking for the minimum deviation between the cumulative sum of simulated and measured TCP-coordinates in the active workpiece coordinate system. The use of these coordinates makes the approach independent from tool change and correction of tool lengths.

$$\sum_{t=t_0}^{t_1} |x_{meas}(t) + y_{meas}(t) + z_{meas}(t)| - \sum_{t'=t'_0}^{t'_1} |x_{sim}(t') + y_{sim}(t') + z_{sim}(t')| \equiv min, \tag{1}$$

where t_0 and t_1 denote the start of monitoring respectively the actual measured machining time step. t'_0 and t'_1 are the corresponding time steps in the simulation domain. This concept guarantees precise and save synchronization while still being robust against small deviations between simulated and measured coordinates at corresponding process steps.

2.3. Modelling

The simulation-based monitoring approach is a two-step procedure. First of all a position based synchronization algorithm explained in section 2.2, is applied. It assigns a specific set of simulation data to every interpolation step of measured machining data. The available simulation data is mapped to the measured signal for every machining interpolation step (online) by a linear regression analysis. That means the measured signal is reproduced on the basis of simulated quantities (covariables). In a second step, again based on liner regression, the probable deviation of the following signal step from this estimate is evaluated. A confidence interval is derived at a certain confidence level. This approach in principle allows for monitoring even processes with varying override which will be tested in further research.

As lined out above it is the aim of the project at hand to derive confidence limits for machine internal signals on base of simulated cutting parameters. A simple linear mathematical model can approximate these signals sufficiently precise.

$$y_n = x_n\alpha + \varepsilon_n, \tag{2}$$

where y_n is a tuple of monitoring signal values at any time step n, which is to be estimated by the model. x_n is the tuple of simulated quantities. This tuple can either consist of only one quantity e.g. the rate of material removal, $x_n = [Q_w]$ or of several different quantities, e.g. the rate of material removal, the depth of cut a_p and the width of cut a_e , $x_n = [Q_w \ a_p \ a_e]^T$. The model coefficient α is determined by the linear regression. It includes physical quantities such as e.g. friction. ε_n denotes the overall deviation from the actual signal value consisting of a measurement- and an estimation error. This model can be parameterized online by a multilinear regression of the sensor signal on base of a certain number of simulated cutting parameters serving as covariables. Thus an estimation of ε is generated and updated in every parameterization step. The model is taught in while machining. That means it gets more precise the more values have already been recorded and are available for parameterization. It needs to be noted that this teach-in can only take process steps into account, which belong to the adequate process segment. I. e. the set of comparable elementary processes as described in section 2.1. Future values can then be extrapolated on base of the corresponding covariables or simulated cutting parameters. The most suitable simulated quantities show a high degree of correlation to the quantity to be measured, i.e. typically main spindle current or tool spindle current respectively.
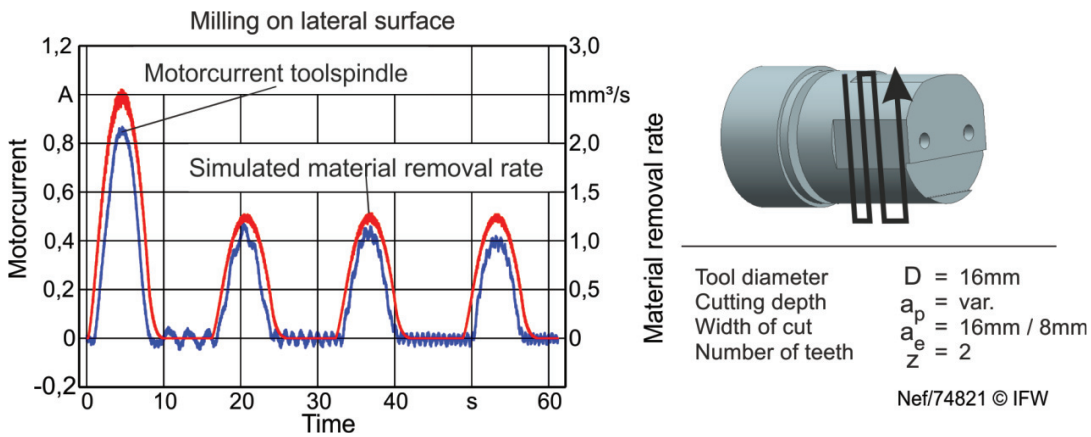

Fig. 3. Comparison between motor current and the simulated rate of material removal. Correlation of the two curves, as indicated here, is a fundamental condition for the regressive approach to be valid.

Fig. 3 compares the motor current of the tool spindle to the simulated rate of material removal in a milling process on the lateral surface showing correlation to a good degree.

During machining, the deviation between estimated and measured sensor values is recorded and serves as a second signal which can again be approximated using a second multilinear model parameterized on the basis of simulation data. Evaluating the overall probable deviation one has to consider both the estimated deviation and the variance due to the regression process. For a large enough set of values taken into account one can assume the deviation to be normally distributed [8], [9], [10]. Subject to this condition a t-distributed quantity can be constructed.

$$\hat{t} = \frac{y_n - x_n \cdot \alpha}{\sqrt{x_n \cdot \beta + x_{\varepsilon,n} \cdot \beta \cdot x_n (X^T X)^{-1} \cdot x_n^T}}. \tag{3}$$

α and β denote the coefficient tuples from the linear regression of the signal, respectively deviation, where α is taken from equation (2). $x_n \ x_{\varepsilon,n}$ are the corresponding tuples of parameters at time step n. X denotes the matrix of parameters at every time step to be taken into account [8], [9], [10]. On base of this quantity confidence limits can be derived which denote a certain range around the expectation value for the measured signal, which is not to be exceeded at a specified confidence level chosen to be $1 - 10^{-5}$ in this work.

3. Application of the Technique

In the following the previously explained process monitoring concept is applied to different turning processes for demonstration. As explained in section 2 a two-step procedure is applied in order to obtain confidence limits for the measurement signal which allow process monitoring. The first step is a simulation based reconstruction of the measurement indicated by red curve in the following. In a second step confidence limits are derived represented by the green curves. These limits are not to be crossed in fault-free machining.

Fig. 4 illustrates the first considered process, a simple cylindrical turning process with a constant depth of cut of 0.5 mm, a constant feed of f=0.35 mm and a constant cutting speed of v_c=140 m/min.
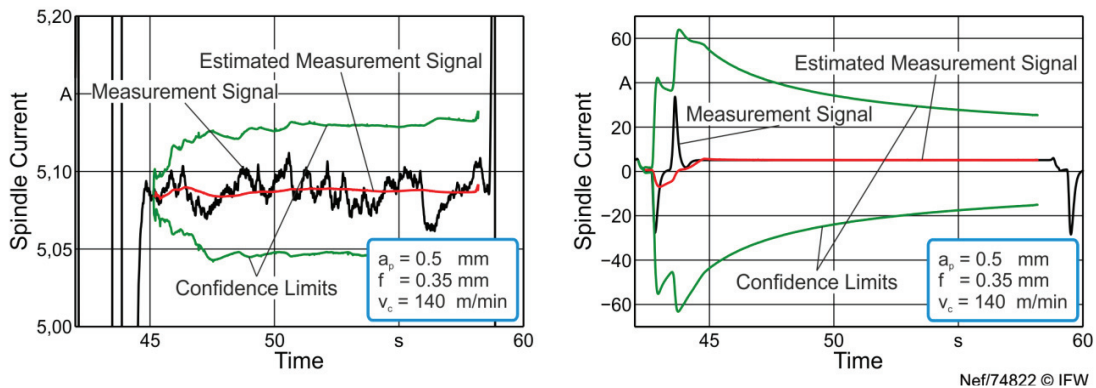

Fig. 4. (a) Cylindrical turning process with constant rate of material removal; (b) Erroneous confidence limits as a consequence of incorrect teach-in region. It is important to start the regression after the correct segment has been entered making segmentation and synchronisation crucial aspects of the simulation based monitoring.

Fig. 4 (a) shows how effectively the estimate maps the measurement signal. It is solely based on one simulated quantity, the rate of material removal Q_w. The width of the confidence interval depends directly on the goodness of fit of the measured signal in the respective region. The more precise the signal prediction, the narrower is the confidence interval. It needs to be noted that the confidence limits correspond to the same confidence level everywhere. Fig. 4 (b) shows the same cylindrical turning process as seen in Fig. 4 (a), monitoring however starts already in the previous elementary process. Thus the teach–in of the linear model covers signal peaks corresponding to tool movement to and from the return plane, a period without tool engagement which is not adequately described by the model. Consequently the high deviations between signal and fit occur and cause very wide confidence limits which are of course useless to monitor the process. This is proof to how important it is to teach in the monitoring algorithm in the valid process segment and to avoid acceleration periods, where the dependence between simulated variables and signal cannot be assumed to be linear.

Fig. 5 shows a second, different cylindrical turning process. At a constant feed the depth of cut varies from 4.0-0.0 mm and in a second cut from 0.0-4.0 mm. Thus the rate of material removal varies. The spindle speed was fixed constant in order to evade acceleration effects. Making use of only one covariable again, the rate of material removal Q_w is shown to be sufficient for monitoring. Fig. 5 (b), a magnification of Fig. 5 (a), shows nicely how precise the approach maps the measurement signal and derives confidence limits. Fig. 5 (b) shows a turning process with constant cutting parameters exhibiting tool breakage. It indicates the spindle current spontaneously rising dramatically and exceeding the Confidence limits which are generated based on the data before breakage. Thus a process error is identified. Moreover, Fig. 5 (b) demonstrates a further interesting aspect to notice, the path of signal estimation and confidence limits in case of continuous teach-in beyond the tool breakage incident. The estimated signal, though at first obviously inaccurate, slowly converges back to the signal. The algorithm adapts to the new circumstances. The new confidence limits however are considerably wider having been influenced by large measured deviations between signal and estimation. Fig. 4 and Fig. 5 indicate the validity of the monitoring

approach at hand covering not only constant but also varying paths of measured signals as far as process segmentation and synchronization between signal and simulation are carried out to a sufficient degree of precision.
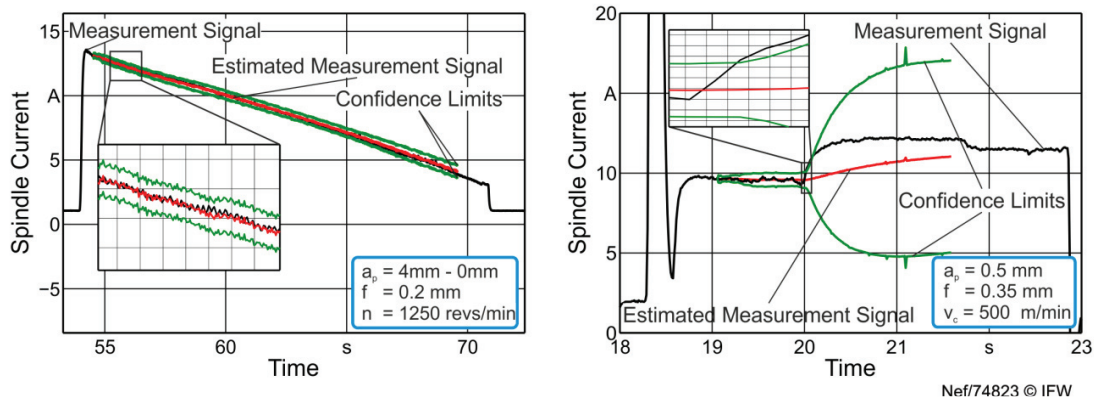

Fig. 5. (a) Cylindrical turning process with variable depth of cut a_p ; (b) Cylindrical turning process with constant depth of cut a_p exhibiting tool breakage incident indicated by the measured signal exceeding the confidence limits.

4. Conclusions and Outlook

The experiments performed and shown above clearly demonstrate the validity of the monitoring approach at hand. Simulation based process monitoring for single item production can in fact be performed without the need for teach-in. It has been shown that process segmentation during work preparation, a concept developed in close cooperation with Artis GmbH, as well as precise synchronization between simulated and measured data during machining is most important to achieve satisfying monitoring results.

The monitoring technique described above is meant to be tested and validated under real machining conditions. It is going to be integrated into an Artis CTM platform, an industrial monitoring solution, in order to monitor real workpieces (Premium Aerotec GmbH) on a R300 turn–mill center (Index Werke GmbH).

Further research is going to extend the monitoring approach to a variety of different kinds of machining processes and to address tool wear.

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