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Autonomous Modular Process Monitoring

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Abstract

Process monitoring is essential to detect process disturbances systematically in cutting machining processes. Hence, it can contribute significantly to process safety and thus to automatized production. Many different monitoring strategies have been developed and successfully tested. However, they usually require some manual parametrization effort by the machine operator and can be difficult to use. Furthermore, they usually focus on very specific process conditions. Therefore, an innovative modular autonomous monitoring system is being developed, which can monitor machining processes in single-item and series production and reduces parametrization effort for the operator to a minimum, thus, focusing on manageability of the system.

Keywords: Process Monitoring, Process Segmentation, Economic Production, Manageability

1. Introduction

In order to improve productivity in manufacturing industry cutting processes in machine tools are increasingly automatized. In order to ensure process safety and thus the realization of economic aims with reduced personnel expenditure, process monitoring plays a crucial role [1]. There is a wide range of production processes, which can

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be dealt with on machine tools. Moreover, there are various application scenarios from single item- to series production. An abundance of different process monitoring strategies have been developed and implemented in order to meet the different arising requirements [2, 3]. It is very challenging to determine adequate features and to define the expected part signatures (i.e. the set course of the respective signal shape) for monitoring. Conventional strategies usually offer the opportunity to monitor very specific processes at sufficient accuracy. However, these systems usually require certain knowledge about the machining signals during fault-free machining. I.e. they need to be elaborately parameterized. Parameterization on the one hand can be time consuming and on the other hand may require expert knowledge. Moreover, in single-item production defining a set course of monitoring signals is difficult because it cannot simply be derived from previous processes of the same kind. This makes single-item production generally impossible to be monitored conventionally. Hence, it is the aim of this publication to line out the development of an autonomous modular process monitoring system for both series- and single-item production, which drastically simplifies the necessary parameterization procedure and so increases manageability for the machine operator.

2. A Modular Process Monitoring System

In order to cover the different process monitoring requirements due to varying machining types a combination of different strategies is to be implemented. A modular process monitoring system meeting these criteria is currently being developed at the Institute for Production Engineering and Machine Tools (IFW) Hannover in cooperation with DMG MORI. It contains modules for both single-item production and series production, which in combination flexibly enable various monitoring tasks performed on the same machine depending on the contemporary requirements. The modular process monitoring system will be able to automatically adjust to the perspective requirements of end users without the need for difficult manual parameterization. For this purpose, an online (i.e. process parallel) process segmentation system has been developed enabling individual treatment of specific process phases and engagement conditions. It is required in both modules to enable the separation of different process types. Moreover, synchronization with historical data in the series production case and the automatic process specific parameterization of the monitoring system is based on this segmentation. Thus, in addition to being a very general and adaptable process monitoring system, easy and effective manageability is also assured.

Fig. 1 shows the overall architecture of the autonomous monitoring system. When a part program is started, the appropriate monitoring strategy is chosen based on whether or not there is a corresponding data set in the database. I.e. whether a single-item- or series production strategy has to be followed. More precisely, the series production

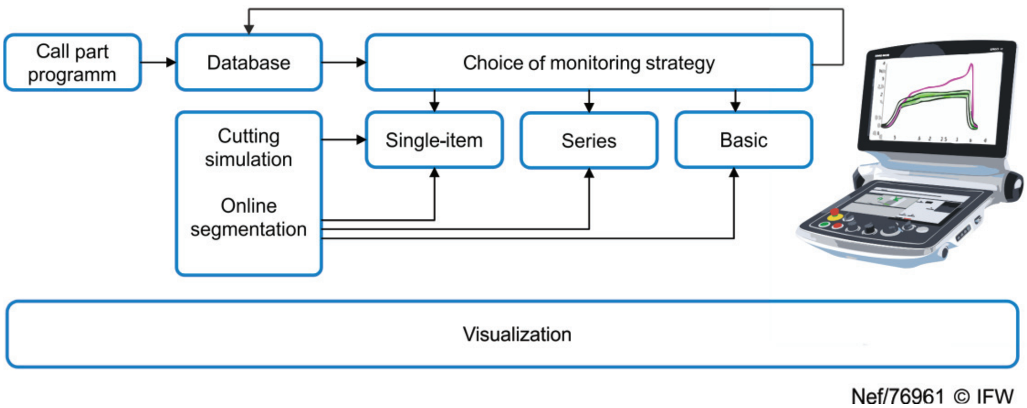

Fig. 1 Modular architecture of the autonomous process monitoring system

module will autonomously be started, if a dataset with the respective name exists and thus there is historical data, that can be made use of to generate monitoring limits. In any case, a cutting simulation software, implemented into the machine control, derives engagement conditions parallel to the process. For this purpose, the overall process is separated into phases exhibiting material removal. These phases are characterized based on information about the active tool and an analysis of the actual tool path. Thus, classification of individual process segments is possible. The system also contains a visualization module showing monitored signals and corresponding monitoring criteria. Process data as well as monitoring results are saved to a database by default in order to optimize the monitoring quality and enable the improvement of the system. Each module will be implemented with default settings enabling autonomous monitoring. Machine operators will also be able to configure certain settings, e.g. the choice of sensor signals or preset monitoring criteria in an expert "view".

In addition to the two sophisticated monitoring modules for single-item-and series production a further, basic monitoring module is developed. A basic but very stable monitoring approach is to be implemented here, which is able to be active for every type of machining. E.g., a tool-specific overload protection will be integrated. The precise configuration of the basic module is currently being developed.

2.1. Cutting Simulation and Process Segmentation

Lacking history data about the respective process machine signals serving as monitoring reference (e.g. spindle torques), have to be simulated in order to monitor single item machining processes. Previous work has relied on offline simulation before machining [4] (i.e. the simulation cannot base on the tool path derived from the machine control and therefore is not process parallel). The advantage of offline simulation of course is that a much higher resolution can be reached as the computation time is not critical. However, On the one hand this beared the disadvantage of a necessary time synchronization between simulated and measured data while machining, which is a potentially error-prone procedure. On the other hand, a virtual machine is necessary, which is able to exactly

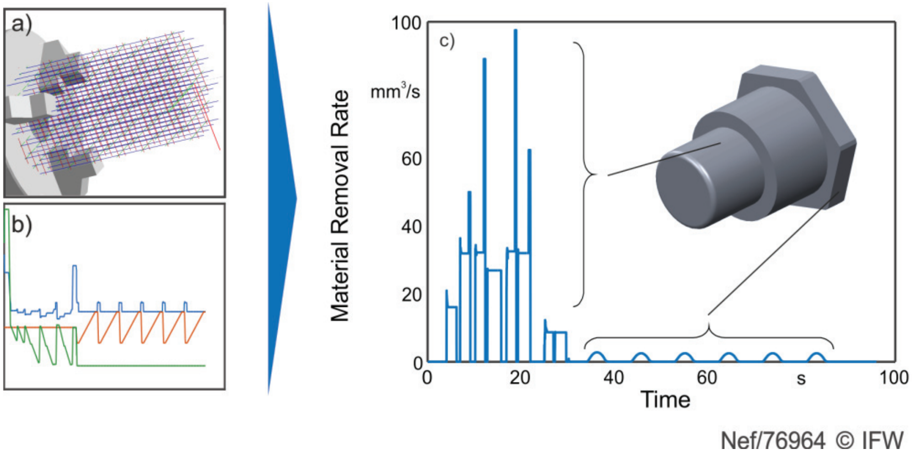

Fig. 2 a) Dexel discretization of the workpiece, b) Toolpath (axis positions of tool centre point), c) simulated material removal rate

simulate the tool paths. Therefore, the research project at hand relies on an online cutting simulation performed parallel to the process. The tool paths can be derived from the machine control. They are not required previous to machining, so a virtual machine is not necessary. All attached simulation steps up until to the generation of confidence limits are also performed online. Thus, measured and simulated data are automatically synchronous. The cutting simulation system calculates tool engagement conditions based on predefined geometry of the raw material, the tool geometry and the tool path, which is derived from the axis positions of the machine from the machine control. The workpiece is discretized in a dexel model with a resolution of 0.5 mm, cf. Fig. 2 a). The object is intersected by a set of parallel rays. The line between two intersection points, fully inside the object, defines a dexel [5]. Engagement conditions are calculated by means of evaluating the intersection of the dexel grid with the tool surface, yielding the actual tool engagement conditions. The tool path is derived by the axes position data provided by the control system within a sufficiently high resolved cycle of 12 ms, cf. Fig. 2 b). Fig. 2 c) shows the resulting simulated rate of material removal corresponding to the production of the depicted workpiece.

Based on the simulated rate of material removal, continuous phases of the process exhibiting tool engagement are identified (segmentation). The individual segments are specified by means of information about the active tool and an analysis of the actual tool path. I.e. The system automatically detects the current type of machining.

3. Single Item Process Monitoring

Customized Single Item Production plays an important role for the machining industry making process monitoring systems in this field commercially desirable. The integrated single-item monitoring module works with a simulation-based monitoring approach. An online cutting simulation system, implemented into the machine control, calculates actual tool engagement conditions parallel to machining (in this case the rate of material removal as well as the depth of cut and the cutting width), cf. section 2.1. The calculated engagement conditions can be used to statistically derive a confidence range for measured spindle and axis torques, which can be used to assess the actual process state, i.e. to detect process errors. Earlier research was able to show, that these data can be adequately simulated within a model with tool engagement conditions as input values[4]. The spindle torques in turning and milling processes for example can in decent approximation be modelled by

$$M = \alpha \cdot Q_w + M_0 \, , \tag{1}$$

where Q_w denotes the material removal rate and M_0 the idle torque without tool engagement for the respective machining process which corresponds to the friction of the drive. Therefore, the basis for simulating machine signals and thus single item process monitoring is a cutting simulation. Acceleration phases are currently not covered by this sort of process model. More sophisticated models, which can also encompass acceleration, are currently being analyzed.

3.1. Monitoring

In single-item production confidence limits for machining signals have to be derived parallel to the process. As a first step the model (Eq. (1)) is parametrized by linear regression with M being the measured signal . The idle torque

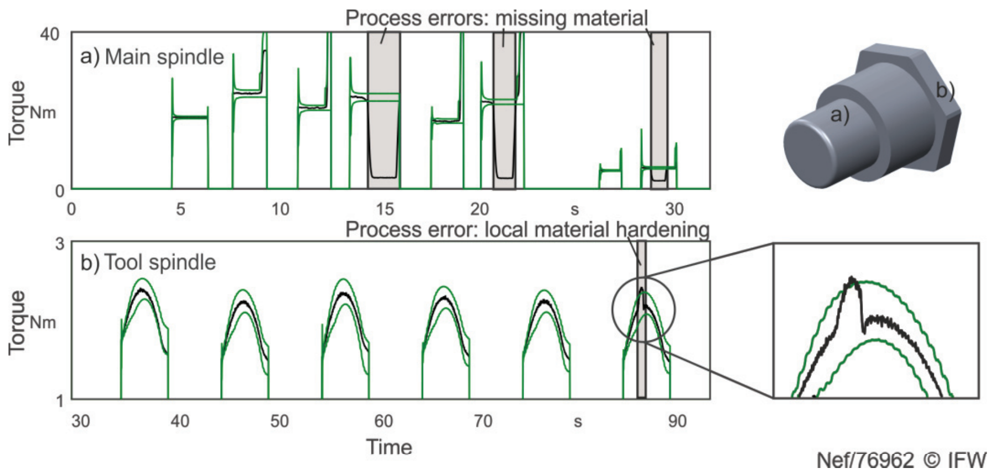

Fig. 3: Online single-item production process monitoring using the example of a workpiece produced in turning (a) and milling (b) segments. The black curves denote the torque of the main spindle (a), respectively tool spindle (b). The green curves denote confidence limits, which are not to be exceeded, respectively undergone. Otherwise, process errors are detected.

M_0 is measured just before the start of the respective segment. For this purpose the torques are permanently measured. If a segment start is detected, the last pre-segment value defines the idle torque The deviation between measurement and model can again be approximated by a liner model based on the rate of material removal such as (1). For a large enough set of data one can assume this deviation to be normally distributed [4]. Following this assumption a t-distributed quantity

$$\hat{t} = \frac{\mathrm{y_n} - \mathrm{x_n} \cdot \alpha}{\sqrt{\mathrm{x_n} \cdot \alpha + \mathrm{x}_{\varepsilon,\mathrm{n}} \cdot \beta \cdot x_n (X^T X)^{-1} \cdot x_n^T}} \tag{2}$$

can be constructed [4]. α and β denote the parameters corresponding to the models for the signal, respectively deviation. They can be calculated by linear regression [4]. x_n and $x_{\varepsilon,n}$ are the respective covariables of parameters at time step n. X denotes the matrix of parameters at every time step. (2) is also valid for multilinear models with α, β, $x_n$and $x_{\varepsilon,n}$being vectors. Based on $\hat{t}$, statistical confidence limits for fault free machining can be constructed with the help of a desired student–t percentile [4]. Fig. 3 shows the application of the described monitoring system to the production of the depicted workpiece. The process consists of turning (a) and milling (b) segments. The black curves denote the measured spindle current of the respective spindle currents. The green curves denote the calculated confidence limits of the process. Exceeding, respectively undergoing these limits corresponds to process errors elucidated by a grey background (missing material (a), local hardening due to stainless steel pin inserted to the aluminum raw material).

4. Series Production Process Monitoring

In series production, the conditions for process monitoring are markedly better, compared to single item production usually historical process data is available and can be used. The standard approach for process monitoring is to declare a certain confidence range around a specific process signal, which is derived by historical process data of the respective signal. However, it has been shown e.g. in [7] that the sensitivity of process errors varies drastically among different signals and diverse process segments. Thus, a multi-criteria approach is preferable to systems which only monitors individual signals. In [7] a multi-criteria process monitoring system is proposed, which is self-adjusting and self-tuning, with regard to the correlation of different signal features towards specific reference features. The system provides a powerful monitoring solution with an automatic parametrization procedure for series production. The required reference features, however have to be defined in advance, which requires a certain amount of expert knowledge. It is the aim of the project at hand to provide a very easy to use, autonomous monitoring system which does not require any expert knowledge. Thus a systematic procedure for feature extraction from all available sensor data is required, which does not depend on any intervention of the machine operator.

4.1. Principal Component Analysis

The principal component analysis (PCA) is a statistical procedure, which converts a set of potentially correlated observations into a set of linearly uncorrelated variables using orthogonal transformation. These uncorrelated variables are called the principal components of the system. They reflect the components of the system containing linearly independent information from each other. Thus, on the one hand, the PCA can be used for an automatic feature extraction in multi sensor systems as can be seen in **Fehler! Verweisquelle konnte nicht gefunden werden.**, where the analysis is applied to a random data set. The PCA automatically finds the orthogonal directions of the system exhibiting the largest variance (i.e. the largest amount of information), cf. Fig. 4 a). The data can subsequently be projected to these directions, corresponding to the principal components of the system. The usability of the PCA for feature extraction in the context of process monitoring has already been reported in [8]. On the other hand, it also serves as a tool to simplify the system by dimension reduction.

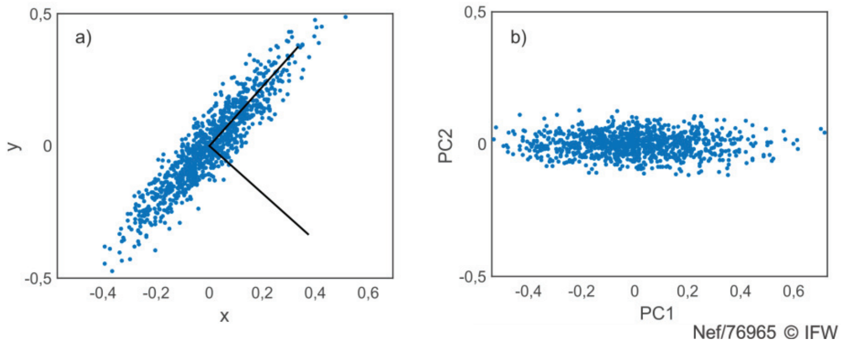

Fig. 4 (a) Random data set representing a two dimensional time series, i.e. information of two sensors; (b) The dynamical system of (a) in principal component representation, i.e. the coordinates are defined by the directions

4.2. Process Monitoring based on Principal Components

The PCA can be used to automatically extract relevant information provided by multiple sensors, respectively the machine control. Thus, it is well suited for signal pre-processing in process monitoring systems. In many cases the first principal component already captures the significant information provided by the different signals. Fig. 5 shows

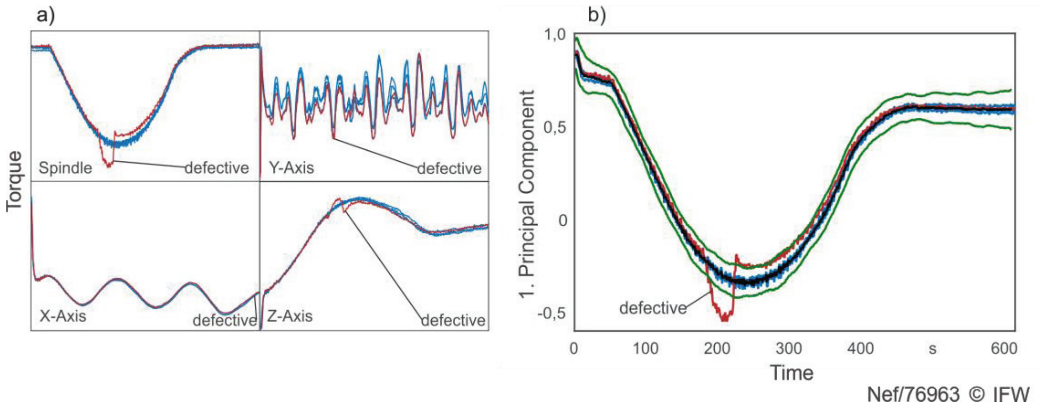

Fig. 5. (a) Spindle torque, x-axis torque, y-axis torque, z-axis torque of milling process; (b) Projection of signals onto first principal component statistically derived confidence limits around the mean values. Blue curves denote fault free machining processes, the red curve corresponds to a defective process exceeding the green confidence range.

how a PCA can be used to extract relevant data from four different signals in a milling process, the spindle torque as well as the torque of the x-, y- and z-axis. Fig. 5 b) shows the projection of these four signals in four consecutive machining processes on the first, and thus the most important principal component. Confidence limits for monitoring further processes of the same kind were derived statistically. Fig. 5 b) nicely shows the detection of a process error (local hardening of the workpiece material) as the defective red curve leaves the confidence range defined by the green curves. The blue curves denote fault-free processes, the black curve the mean value of all fault-free processes.

5. Summery and Outlook

To sum it up, a powerful, versatile and easy to use process monitoring system is proposed, which will automatically adept to the actual process types and requirements. The system will be implemented into the machine control of a DMG MORI NTX 1000 2nd generation machine tool serving as a system demonstrator. The most important aspect of the system is its modular character. Different modules, individually very well suited to specific monitoring requirements, are combined into one autonomous system. They share special basic components with each other, which significantly simplifies the development of a powerful overall system and enable a simple system structure and maintenance possibilities.

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