Control-System-Based Approach for Robust Process Monitoring in Single Item Production

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Summary: Process monitoring systems are used in production processes to identify disturbances. Until now, they are primarily used in mass production. This paper presents a new teach-less monitoring approach for milling processes. The algorithm is based on measured drive- and control-inherent signals of a machine tool. In order to guarantee a robust strategy the engagement of the tool and the machine conditions were taken into account. For this purpose model-based approaches were realized. The evaluation of actual data in a material removal simulation leads to a perfect synchronisation between simulation and measured drive-and control-inherent signals.

Keywords: Machine Tool, Monitoring Strategy, Control System, Simulation

1. Introduction

Globalisation and the related efforts to ensure the competitive ability of a high-wage country require the production of high quality goods while at the same time manufacturing costs must decrease [1,2]. The relevance of quality assurance is rising. The aim of today's modern quality assurance is to produce quality products (in-process-control) and not subsequently trying to prove the results after they have been produced (post-process-control) [3,4].

The configuration of currently installed process monitoring systems is time consuming. They can only be applied cost-effective in batch production [8]. Using the classic teach-in-method, dynamic envelopes can be parameterised by reference processes.

Over the past years industries from the field of single item production like the aircraft industry or mould and die design show an increasing demand on process monitoring systems [1]. An economic production, while simultaneously increasing workpiece quality is one reason. To give a solution for those industries new strategies for single item production must be developed [5]. Approaches that have been studied can be divided into two groups. Signal- and feature-based approaches are one possibility to parametrize limits without using the teach-in method [6]. These approaches were already used in industry. Model-based methods, which include for example the simulation of process forces, present the state of research [5]. Using the functionality of customer open architecture, drive- and control-inherent signals are typically used for process monitoring solutions in industrial environment [4,6,7]. Internal sensors normally demonstrate a decreased sensitivity, amplitude and time resolution compared to external sensors (e.g. dynamometer, accelerometer). At the same time they cause lower costs and a reduced susceptibility to failure. Further, external sensors in the flux of force can lead to a reduction of stiffness of machine tool and a limitation of working area. This leads to a reduced customers' acceptance.

2. Concept

The strategy presented in this paper is a new approach which allows monitoring processes and tools in single item production. It fulfills a variety of industrial requirements. The general idea is to structure the process into small segments according to the engagement of the tool. Then each new measured value can be evaluated in dependence to the underlying information (condition-based). To avoid false alarms, friction- and inertia-based disturbances (e.g. spindle acceleration, no-load current) of the machine axes were taken into account. The incoming internal sensor signals, the engagement of the tool and the conditions of the machine were evaluated in a multicriterial decision making system (logic).

The following chapters describe empirical studies concerning the sensitivity of the incoming sensor signals, the development of a state observer to determine the engagement of the tool and an approach for systematic setting of monitoring limits in a teach-less strategy.

In chapter 3 the potential of signals from modern customer open control systems were systematically analysed in terms of their sensitivity to process failure, process parameters, process operation conditions and disturbances from the machine tool structure and control system.

To ensure robustness against false alarms, a model-based approach was developed. It identifies on-line the engagement of the tool and provides it to the process monitoring system (chapter 4). For this a material removal observer was developed, which evaluates the real data of the control system.

Based on the output of the material removal observer, a new method for condition-based setting monitoring limits to incoming sensor signals is presented. The considered input signals are the main spindle current (I) and the control deviation of the feed axes (R). The robustness of the approach has been improved by the consideration of specific machine-related states. A focus is on the self-adjusting character of all operating parameters.

3. Sensitivity analysis

Drive- and control-inherent sensor signals are analysed in terms of process monitoring. Their signal amplitudes show a high influence of process and machine. The goal is to derive automatisms for teach-less identification of process faults (e.g. unstable processes, tool breakage, tool wear). Therefore the signal peaks have to be evaluated on the basis of the actual tool engagement and machine condition.

All signals have been measured, using the SIEMENS compile cycles via Profibus™, with a monitoring platform of the Institute of Production Engineering and Machine Tools (IFW). To avoid overloading the PLC Programmable Logic Controller (PLC), data rate was limited to 100 Hz. In systematic studies, the signals of the compile cycles were compared to signals of a force sensor. These studies show that especially the feed axis control deviations have a high sensitivity towards unstable processes. In addition, these signals also have a potential for tool breakage monitoring. This allows the extension of the well-known control-based monitoring of the spindle current by a new, non-redundant monitoring signal. Other studies show that the spindle current gives a very high correlation to the material removal rate. In order to use this characteristic for a teach-less monitoring approach, the spindle current signal has to be corrected by the influence of inertia and friction. The main disturbance to the control deviation of the feed axis is the influence of inertia during accelerated periods with high jerk. To implement a teach-less process monitoring strategy the disturbances must be identified parallel to the process and need to be considered in the monitoring algorithm.

4. Material removal observer

In addition towards the sensitivity to process failures, the internal sensor signals show a sensitive behaviour when tool engagement condition changes. An intelligent process monitoring strategy must be able to distinguish a change in the tool contact conditions from process failure.

This chapter describes the development of a material removal observer which detects the tool contact conditions parallel to the milling operation. This approach aims to compensate the disadvantages from the state of the art known model based approaches for teach-less process monitoring strategies. The output is used for parameterising the envelopes for monitoring internal control sensor data without using a CAM (computer-aided manufacturing) system. Further the synchronization of simulated envelopes and actual sensor data is always accurate.

For this purpose a dexel-based tool and workpiece model has been implemented on the monitoring platform. The geometry of the tool is simplified modeled as a cylinder, using the bounding box method. To derive the cutting conditions the dexel-field of the tool has been divided into functional areas. The approach receives a great flexibility by evaluating the set-positions and -velocity values ($x_{i\ set}, \dot{x}_{i\ set}$) of each feed axis (i) generated in the NC on-line. Figure 1 describes the connection of the material removal observer to the NCU of a machine tool. Furthermore the output vector is pictured. It describes the tool engagement as binary condition and the material removal rate with floating point precision.

Figure 2 compares the calculated removal rate (Q) with the measured process-oriented spindle current (I_P) in a pocket milling process.

The signal path of the removal rate (Q) shows a very high correlation to the measured spindle current signal in the accurate running process. It demonstrates a great potential for the direct comparison of the measured spindle current and the simulated material removal rate. The deviation of the signal characteristics are therefore an indicator of process disturbances.

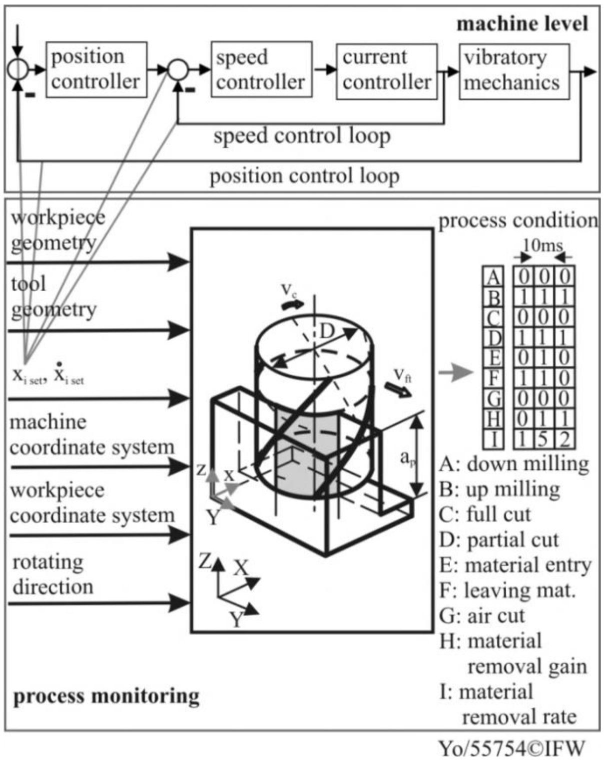

Figure 1. Connection of the material removal observer to the NCU of a machine tool.

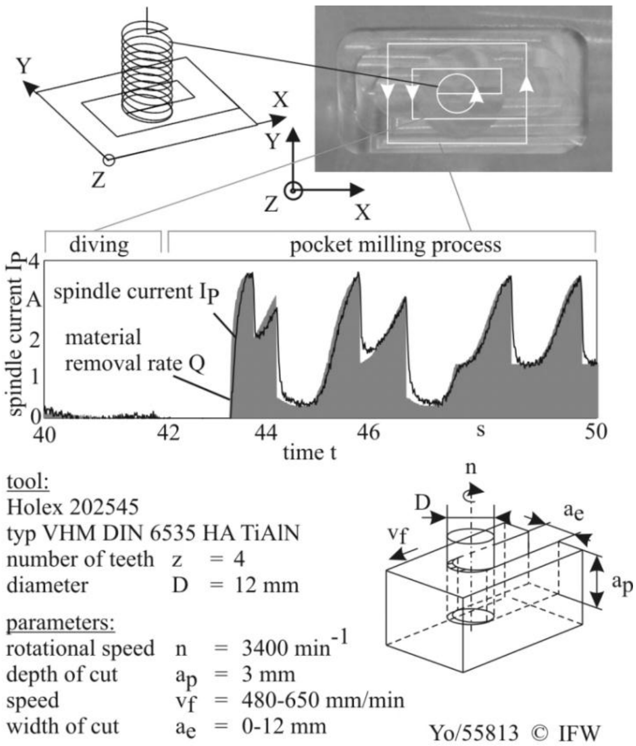

Figure 2. Comparison of the spindle power with the continuously output of material removal rate.

5. Monitoring strategy

Based on on-line computed tool engagement conditions a strategy for monitoring the feed axis velocity control deviation (R) is presented. As part of a multi-dimensional decision making system, an autonomous monitoring of the spindle current (I) was implemented as well. This uses the correlation of material removal rate and the spindle current to calculate the monitoring limits.

Before the process can be evaluated each incoming measured value of the feed axis control deviation (R) is preprocessed in three steps (

Figure 3):

1. Compensation of process-independent disturbances (e.g. influence of inertia during the acceleration of machine axes).
2. Signal processing using a feed rate dependent RMS to smooth the noisy signal.
3. Systematically parameterisation of dynamic limits [6].

In order to parameterise the dynamic limits, the output values of the material removal observer and the machine conditions were classified in terms of their effect to the signal. Depending on the state of the classified process and machine conditions and the current operation parameters, the dynamic and the distance of the limits are parameterised on-line.

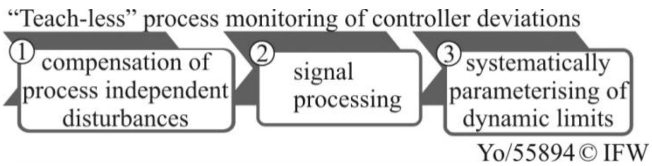

Figure 3. Approach to teach-less process monitoring of controller deviations.

Figure 4 compares the new condition-based approach with common statistic-based dynamic limits. At time t =30,2 s the material removal rate changes. The reason for this is a change of cutting condition from partial cut to full cut. This leads to a sudden change of the signal amplitude of the control deviation of the feed axis R. With the knowledge about the change in process, the dynamic parameters of the limit can be adapted and a false alarm is prevented. In comparison,

Figure 4b illustrates the behaviour of the well-known dynamic limits which calculate the distance between a measured signal and the monitoring limit statistically. The sudden change in process leads to a border collision and thus to a false alarm. The presented strategy is on the one hand sensitive against process failures like chatter and tool breakage and on the other hand robust against false alarms because of changing state of process or machine.

6. Conclusion and Further Research

This paper describes a multicriteria process monitoring strategy for single item production. It demonstrates how limits for monitoring drive- and control-inherent sensor signals were set by analysing the current process parameters, tool engagement and conditions of the machine. This strategy allows detecting unstable processes and tool breakages.

Future research is focused on expanding the strategy to monitor tool wear. Again the segmentation of the process into small section will be basis for the monitoring strategy.

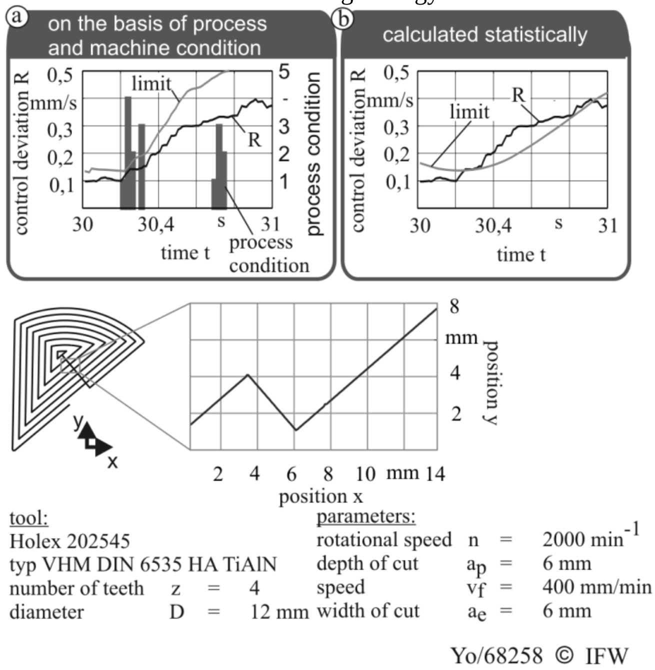

Figure 4. a) Dynamic limits: calculated on the basis of the process and machine conditions, b) Dynamic limits: calculated without consideration of process and machine conditions.

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