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Self-tuning of teachless process monitoring systems with multi-criteria monitoring strategy in series production

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Abstract

Modern monitoring systems in machine tools are able to detect process errors promptly. Still, the application of monitoring systems is restricted by the complexity of parameterization for save monitoring. In most cases, only specially trained personnel can handle this job at multi-spindle machines or turn-mill centers. The aim of the research project "Proceed" is to figure out in which extent a self-parameterization and independent optimization of monitoring systems in industrial series production can be realized. Therefore, the complete parameterization of the processing chain, consisting of the choice of signal sources, character extraction, the monitoring- and decision making strategy, shall be automated. This paper deals with the self-parameterization of a multi-criteria monitoring system based on a genetic algorithm.

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Keywords: Self-optimization; process monitoring; machine tool; series production

1. Introduction

Monitoring systems in cutting machine tools shall observe the manufacturing process and identify process errors such as critical wear or breakage of the used tool. Therefore, the motor current of spindle and feed drives as well as additional sensor signals such as acceleration, force or acoustic emission signals are monitored [1]. A large part of monitoring strategies used in series production are attributable to time dependent monitoring limits, which are based on the initial manufacturing process [2, 3]. If a monitored signal exceeds its threshold, the monitoring system sends

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an error message to the machine control. These can cause an immediate stop or a tool change. Thus, secondary damage can be avoided and the availability of the machine tool increases. In order to configure the monitoring, signal sources as well as extraction methods and monitoring strategies have to be defined. Thereby, time effort and complexity increase with the number of monitored signals and the extent of the machining. So the monitoring parameterization for a process with six-side machining in a turn-mill center is a time consuming task which can only be handled by specially trained staff. Previous approaches to reduce manual effort use statistic confidence limits to derive monitoring limits automatically [4, 5].

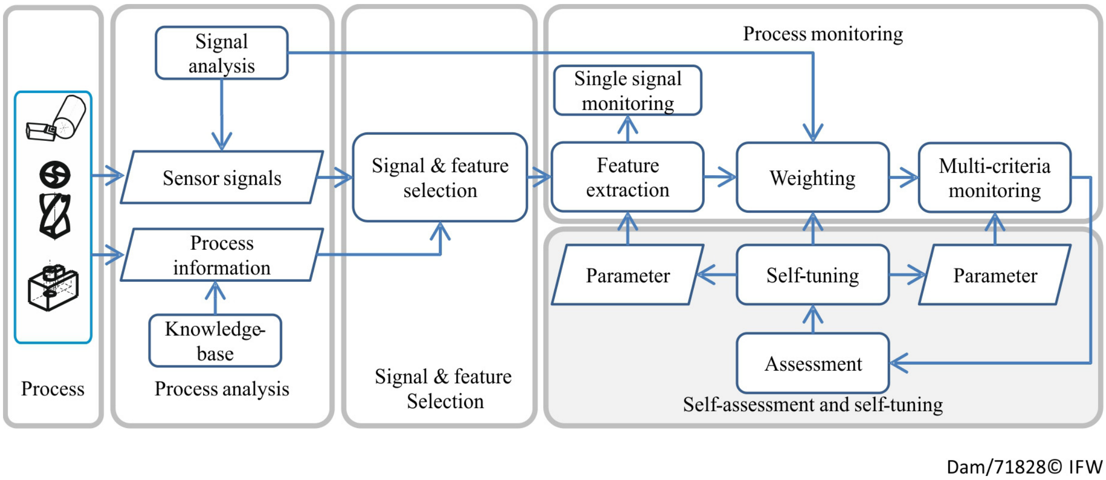

Fig. 1. Information flow of the complete processing chain of the self-adjusting approach.

However, the parameters of feature extraction, like cut-off frequency and filter order, have not been regarded for online parameterization. In [6] an approach for a pre-process design of monitoring systems is presented. At this point the project Proceed wants to figure out, in which extent a self-parameterization and independent optimization of monitoring systems in industrial series production based on historical data can be realized. Figure 1 gives an overview about the information flow in the complete approach. The aim of the project is to develop a self-adjusting and self-tuning process monitoring system, based on multi-criteria sensor signal evaluation, which is able to assess monitoring quality quantitatively. This is intended to ensure reduction of manual parameterization and improvement of monitoring quality. This paper deals with the issue of the self-tuning. In a first approach it is assumed, that the signal sources and feature extraction methods are already defined. In the application scenario signals and feature extraction methods are selected based on analyses of the signal characteristic from previous manufacturing processes [7]. Thus the parameters of feature extraction and threshold building are target of optimization. In the application the monitoring starts with a default setting and stores the sensor data. The scattering of the sensor around their long term mean value corresponds to the t-distribution [5]. The data sets are delivered to the optimization algorithm as soon a defined number of data sets are collected. A suitable number is between 10 and 30 datasets. For more than 30 datasets the t-distribution can be replaced by the normal distribution. For less than 10 datasets the uncertainties become too large for representative results. Based on this historical data the monitoring system is tuned. Assuming that the number of considered data is significantly smaller than the number of work-pieces manufactured with one tool set, an optimization can be performed with historical data. At the beginning the monitoring task is performed with default values. At the same time the optimization algorithm searches for an improved setup. Whenever a better setup is found the old one is replaced at the start of the next manufacturing process. The structure of the used monitoring system is shown in Figure 2. From n signals m features were extracted. Based on the single signal evaluation of these features, the process is monitored. The optimization problem can be described generally as follows. The features f are extracted with the extraction methods E from the signals s. The properties of the extraction method, such as cut-off-frequency and order in case of a low pass filter, are defined in the parameter vector x. The feature signal itself is a sum of two components, the true signal sequence g and noise e (1).

$$f_m = s_n \cdot E_m(x_m) = g_m + e_m \quad (1)$$

Each feature is smoothed with a filter defined through the parameter vector y. The signal sequence itself can be described by its mean value over time and its variance (2). Each smoothed feature $f´$ is evaluated with a function E. The characteristics of the evaluation results are dependent from the parameter vector z. It includes the parameter for the single signal evaluation, and the mean value and variance of the smoothed feature $f´$ (3). Finally all evaluations are combined to an overall assessment which represents the estimated condition of the manufacturing process (4).

$$f_m` = f_m \cdot H_m(y_m) = f_m(mean(f_m`), var(f_m`)) \quad (2)$$

$$E_m = E_m(mean(f_m`), var(f_m`), z_m) \quad (3)$$

$$A = A(E_1, E_2, E_3, \dots E_m) \quad (4)$$

The characteristics of this overall assessment, sensitivity and robustness are the quality factor of the optimization. So the quality factor is depending on the given characteristics of the sensor signals and the parameter of feature extraction, smoothing and single signal evaluation. The parameter vectors x, y, and z are the optimization object. The main challenge is the mathematical description of each single optimization problem. Due to the complexity and the number of variables an analytical solution is not practicable [8]. Thus an iterative numeric algorithm is preferred. Since the procedure should be independent from the used extraction, smoothing or evaluation methods it is not possible to predict the amount of local optima of the cost function. Therefor a genetic algorithm, implemented in the MatLab global optimization tool-box, is used for the optimization procedure. A genetic algorithm is a population based optimization algorithm, which is inspired by biological evolution [9]. Since it is a meta-heuristics method the solution may not necessarily present a global optimum. But it allows to find a satisfying local optimum. As a result it is possible to optimize sensitivity and robustness of the monitoring approach to a given behavior. As signal sources, control internal information with typically low sample rates and external sensors with high sample rates are used. Testing machine is a CTX420l universal lathe.

2. Parameterization with genetic algorithm

The start setup for feature extraction and limit formation is generated randomly by the genetic algorithm for a number of 100 individuals. Each individual contains the whole parameter set for the monitoring chain. For each

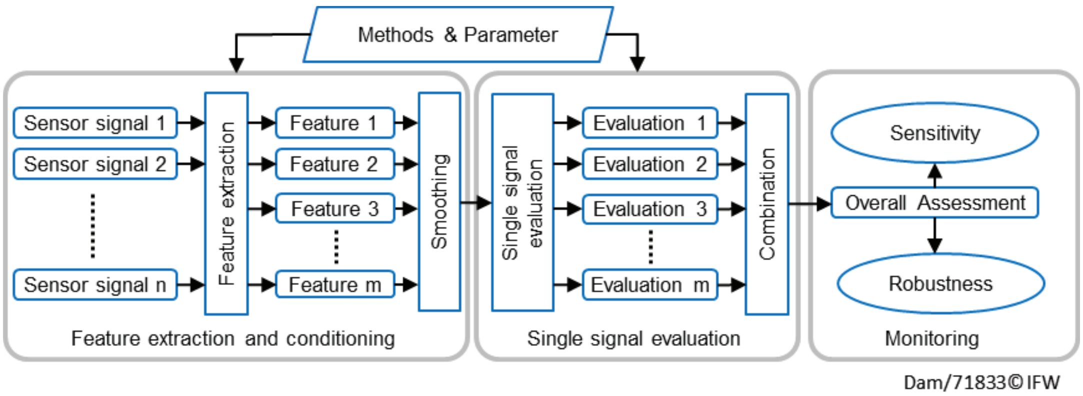

Fig. 2. Structure of the used monitoring system.

individual the monitoring is performed for all data sets. According the fitness of this individual, the quality of monitoring, is assessed. The assessment for each individual is returned to the genetic algorithm which generates a second generation of individuals through crossover of the individuals with a good assessment, which are assessed again. These steps are repeated, until a fixed generation number is reached, or no improvement is detected.

2.1. Used features and parameters

The suitability of this approach was analyzed regarding turning, milling and drilling processes. For all three kinds of machining, process data with and without error was included. Table 1 lists the processes with their parameters and the number of data sets for error free and faulty processes.

Table 1. Examined processes and number of variable parameters for optimisation.

Processes	Number of processes	Number of process errors	Cutting speed	Feed rate	Number of variable parameters
Cylindrical turning	9	2	500 m/min	0,35 mm/rev	7
Drilling	15	4	60 m/min	0,07 mm/rev	7
Face Milling	8	6	175 m/min	0,04 mm/z	19

The last column shows the number of parameters for optimization contained in each individual of one generation. A dataset is classified as faulty if it differs considerable from the majority. Within the turning and drilling processes the process errors are caused by critical tool wear. In the drilling process the tool failure influences four processes. In the milling process -face milling on a cylindrical surface- an error occurred because the tool was pulled out from the chuck about two to three millimeters. The depth of cut in the milling process is a half millimeter. The milling tool was a cutter with a diameter of 16 millimeter. The drill used in the drilling process has a diameter of 6.8 millimeter. Table 2 lists the extracted features and their sources as well as the parameters applied for feature extraction. Used extraction methods are low- and band pass filters, time derivation, single-level wavelet decomposition and signal smoothing. For smoothing an EMA-Filter (exponential moving average) was applied.

2.2. Single signal characteristics and overall assessment

To construct borders for the individual signal sequences three standard methods were used. These are dynamic borders, part signatures [2] and statistic borders [5]. In the course of the analysis it became clear, that it is not possible to detect all errors existing in the datasets with dynamic borders. So, these were not considered further. At part signature limits the monitoring limits are based on the signal sequence of the first manufacturing process. Variables for the parameterization are the upper offset, the lower offset and the shift range. The offsets describe the distance between the first signal sequence and the upper and lower limit. The shift range describes the tolerance of the monitoring towards time mismatch. Statistic borders are based on the variance of the signal sequences over time. With the help of mean value, variance and confidence level confidence limits are calculated.

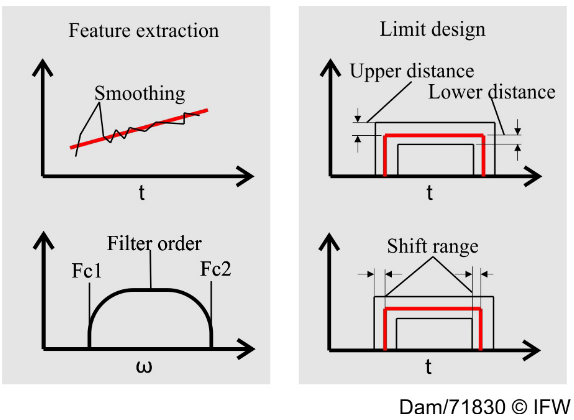

Fig. 3. Overview over the parameters.

Table 2. List of used features with their parameters included in the adjusting algorithm.

Processes	Signal source	Feature extraction	Parameter	Number of Parameters
Cylindrical turning	Torque main spindle	Low pass filter	Cut-off frequency	1
	Torque drive, feed direction	Low pass filter	Cut-off frequency	1
	Torque drive, passive direction	Low pass filter	Cut-off frequency	1
Drilling	Torque tool spindle	Low pass filter	Cut-off frequency	1
		Time derivative/smoothing	Coefficient smoothing	1
	Torque drive, feed direction	Low pass filter	Cut off frequency	1
Face Milling	Torque tool spindle	Wavelet/smoothing	Coefficient smoothing	1
		Low pass filter	Cut-off frequency	1
	Torque main spindle	Time derivative/smoothing	Coefficient smoothing	1
	Acceleration sensor	Three band pass filters/smoothing – Rotational speed – Tooth engagement frequency – First harmonic of tooth engagement	Filter order, Upper cut off frequency Lower cut off frequency Coefficient smoothing	12

Unlike the method of [5], an upper and lower offset is used, which makes it possible, to generate asymmetric limits. Altogether there are four combinations (Table 3) for the methods of monitoring and overall assessment, which were applied for optimization of monitoring of all processes. To get normed characteristics from each individual feature evaluation, based on its limits, the distance between expected value and actual value is divided by the distance between expected value and monitoring limit. The expected value is given by the mean value of the available signal sequences. This normed characteristic describes the amplitude of each feature with a value between zero and infinity. Zero means, that the feature data is equal to the expected value. A one -and each value above- indicates, that the feature crosses the limit. For a transparent result two simple methods were used to get an overall assessment from all single signal characteristics, the mean value and the product of the single feature evaluations. The mean value is meant to represent a robust assessment and the product a failure tolerant assessment. The extreme value for the overall assessment is one. An assessment larger than one will be considered an error. Figure 4 shows the process of creating the overall assessment. In Figure 4a the signal sequences for the second feature in the drilling process with one error sequence is displayed. Figure 4b illustrates the calculation of the normed evaluation value. Figure 4c presents the statistic distribution for the overall assessment of all error free drilling processes.

Table 3. Method combinations for monitoring strategy and used parameters, tested with the optimization.

Threshold value generation	Overall assessment	Parameters
Part signature	Mean value	Upper offset, lower offset , shift range
Statistic threshold	Mean value	Upper offset , lower offset , shift range, confidence level
Part signature	Product	Upper offset , lower offset , shift range
Statistic threshold	Product	Upper offset , lower offset , shift range, confidence level

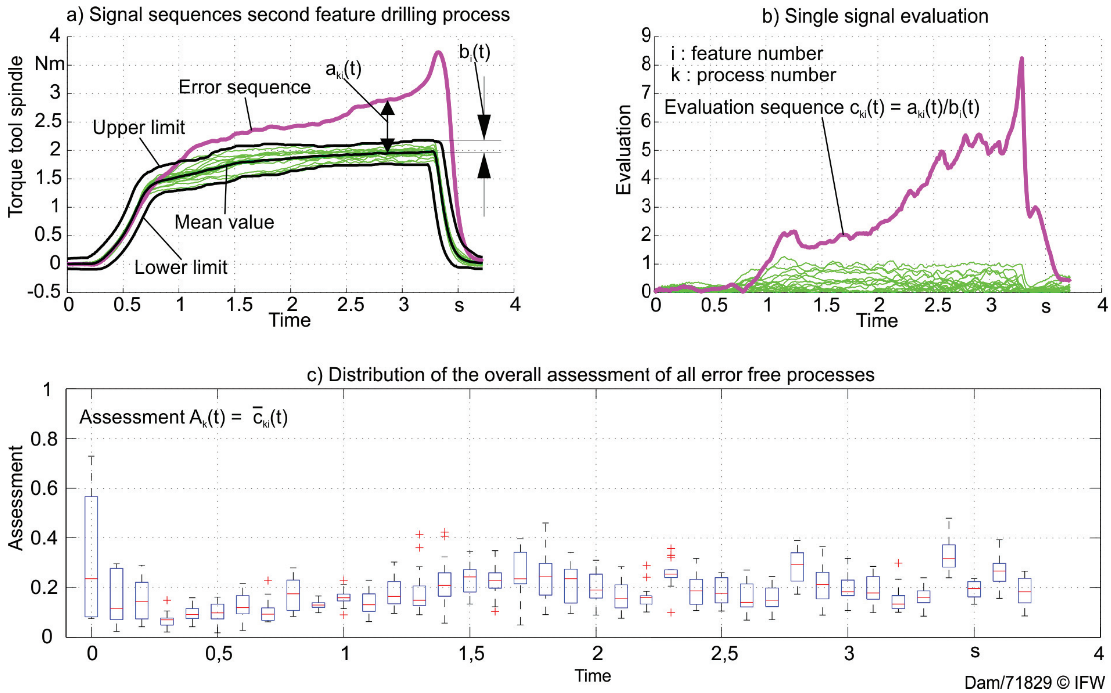

Fig. 4. Result of self-adjusting with a set-point of 0.2 for the overall assessment for part signature with mean value.

2.3. Fitness Evaluation of the monitoring system

The method combinations were applied for all three kinds off machining given in Table 2 for the corresponding features. To evaluate the fitness of each individual, representing a setting, three requirements to the multi criteria optimization approach were defined:

- false alarms must be avoided
- It should be possible to influence the monitoring sensitivity.

- errors should be detected as quick as possible

The first requirement -to avoid false alarms- was implemented by a penalty in the evaluation of the data set. In case of a false alarm the evaluation result for the setup is reduced. Similarly, in the evaluation of error free processes, a deviation of the overall assessment from the set point is penalized. As set point the quadratic mean of the assessment is given. So the optimization algorithm tries to find a solution were errors are detected and the assessment for error free processes tends to a set point. For an evaluation of the reaction time the time of occurrence for each error was determined manually. Then, the time between error inception and error detection will be rated -from zero milliseconds (immediately) to 500 milliseconds- with a value between zero and one. With these three values the fitness of each individual is evaluated. The mean of these three values builds the fitness evaluation for the genetic algorithm.

3. Results

The results of the parameterization are demonstrated by the drilling processes. The generated limits are close to the signal sequences. In the error free processes particular exceeding of the limits occur, but cause no false alarm in the overall assessment, because the overall assessment is lower than one. At the overall assessment with mean value, a set point of 0,2 for the assessment of error free processes was defined, for the threshold building with product a set

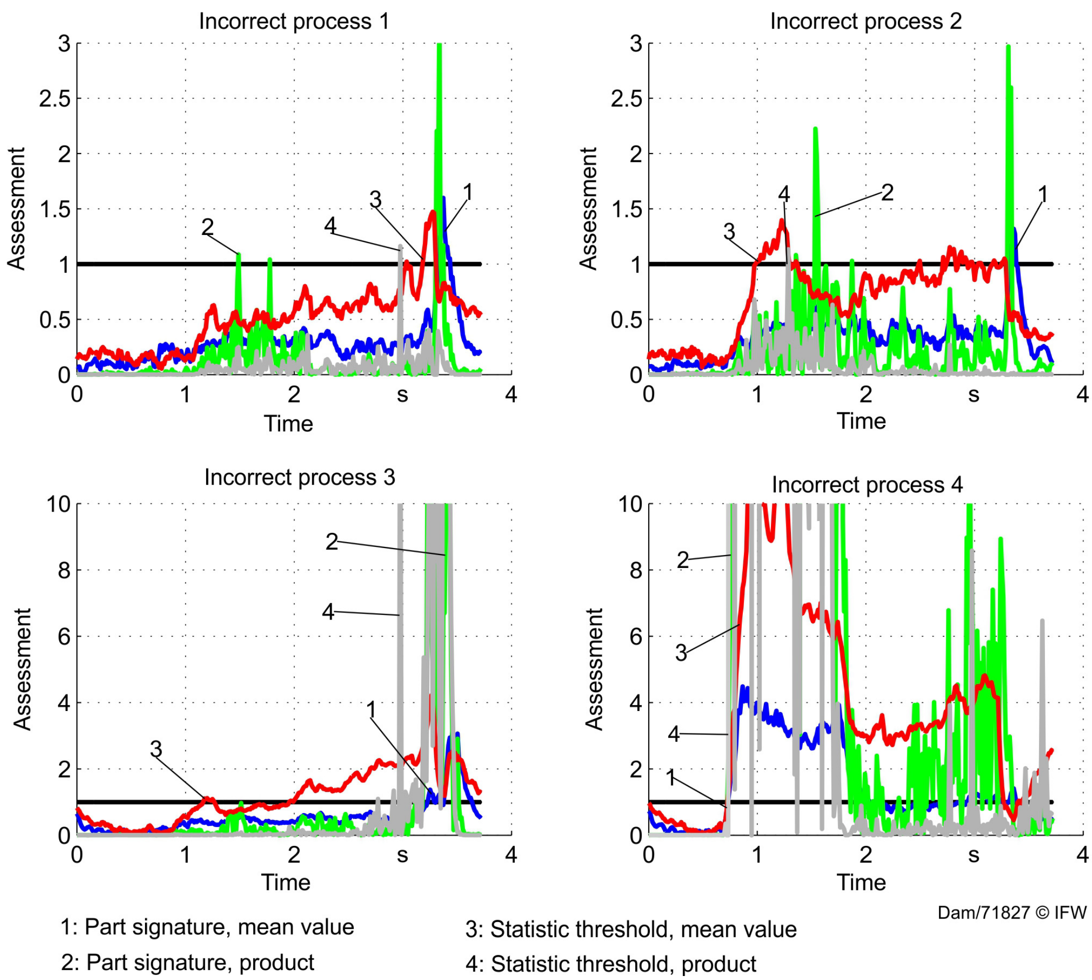

Fig. 5. Overall assessment of error processes for all applied method combinations

point of 0,05 was fixed. The setup with statistic border and mean value get a quadratic mean value of 0,18 and the setup with statistic borders of 0,25. The result for the overall assessment with product is 0,045 for part signature and 0,0075 for statistic borders. The deviation for the last combination can be explained with the rating of the last error free processes. The rating for this process is considerably larger than the rating for the first processes. Since the penalty for a false-alarm weighs more than the penalty for the deviation from the set point in the overall assessment, the genetic algorithm generates a solution, where the maximum value of this assessment is lower than the limit. The reason is that the penalty for an overstepping is a binary decision. The penalty for a deviation from the set point is a continuous function. In Figure 5 the assessment with the same setting for the error processes is shown. Generally all four combinations are able to recognize the errors. The degree of limit exceeding at the error processes rises from the first error till the last error. But because of the robustness of setting four, in consequence of the assessment of the last error free process, the solution found by the genetic algorithm seems to be a specific solution for only this case. The overstepping occurs at error one and two only for one time step. The genetic algorithm generates a proper solution to the fitness function, not for the aim of the requirements, which the fitness function should represent.

4. Conclusion and outlook

It has been shown that it is possible to construct a weighing function, which allows using the method of a genetic algorithm for optimization of the signal processing chain in multi-criteria monitoring systems for machine tools. For this research milling-, turning-, and drilling processes were considered. The potential of the presented approach were tested for rudimentary monitoring setups with three simple features and complex setups with a high number of features and sensor signals with high sample rates. The presented requirements, implemented in the fitness evaluation seem to be suited to define the characteristics of the resulting monitoring. With the presented approach it is possible to realize a self-tuning multi-criteria monitoring system. This allows replacing time-consuming manual parameterization of monitoring systems in the series production by a self-tuning system. However, it is necessary to limit the variance at the assessment of the error free processes in future work. Furthermore, it seems important to include the dimension of overstepping in faulty processes in the assessment. In order to simplify the assessment for the reaction time, artificial errors will be used. To generate such errors, the signal sequences of error free processes are multiplied in a certain time window with special functions, such as steps, ramps or pulses. To reduce the amount of computation, known optimization solutions for frequently used signal processing methods should be implemented, for example self-tuning algorithms for signal smoothing [10]. At this point, the authors would like to thank the German Research Foundation (DFG) for its support of the research project Proceed (DE 447/96–1).

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