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Self-adjusting Process Monitoring System 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 especially for multi-purpose machines. The aim of the research project “Proceed” is to figure out in which extent a self-parameterization and autonomous optimization of monitoring systems in industrial series production can be realized. Therefore, a self-adjusting and self-tuning process monitoring system for series production has been developed. This system is based on multi-criteria sensor signal evaluation and is able to assess its monitoring quality quantitatively. For this purpose, the complete process chain of parameterization has been automated. For series production it is assumed, that the first process is not defective. So, process sensitive features are identified by a correlation analysis with a reference signal. The reference signal is selected through an analysis of the process state by an expert system. To assess the monitoring quality resulting from automatic parameterization, normed specific values were used. These values describe the monitoring quality with the help of the distance between a feature and its threshold normed to signal amplitude and noise. A second indicator is the reaction of the monitoring system to a synthetic error added to signal a sequence. Thus it is possible to estimate monitoring quality corresponding to automatic parameterization. The validation is carried out by a comparison between the result of the assessment and the reaction ability of the monitoring system to real process errors from milling, drilling and turning processes.

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Keywords: Monitoring; Process; Intelligent;

1. Introduction

One objective of monitoring systems in cutting machine tools is to observe the manufacturing process and identify errors such as critical wear or tool breakage for example. Often the motor current of spindle or feed drives as well as additional sensor signals such as acceleration, force or acoustic emission signals are monitored. In [1, 2, 3] an overview of suitable sensor signals for process monitoring and signal processing methods is given. A large part of the monitoring strategies used in industrial series production are attributable to time dependent monitoring limits, whose parameterization is based on the initial manufacturing process [4]. If a monitored signal exceeds its threshold, the monitoring system sends an error message to the machine control. This 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 system, 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 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 [5, 6]. However, the parameters of feature extraction, such as cut-off frequency and filter order, have not been adressed for online parameterization. In [7] 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 can be realized. 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 its

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monitoring quality quantitatively. The intention is to ensure the reduction of manual parameterization and an improvement of monitoring quality. To warrant a deferred applicability, positioning of sensors will be made under the aspect of industrial environmental conditions. Direct force measurements utilizing dynamometers are only used as reference. Figure 1 gives an overview about the information flow in the complete approach.

manufacturing were a cutting process is possible and the feed direction, or the main feed axis is constant. This identification is based on the ID of the used tool and an interpretation of the movement of the feed axes. A distinction between roughing and finishing tool based on the tool ID is possible So the basic kind of manufacturing process is known. For further differentiation the movement of feed axes is analyzed.

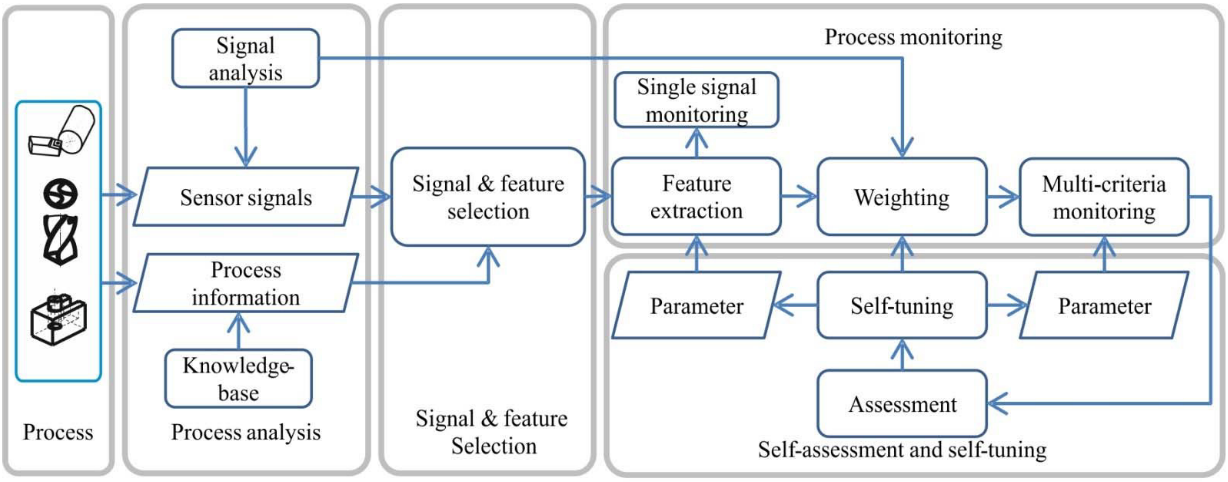

Figure 1 Information flow in the complete processing chain

First Step is an analysis of the first manufacturing process and its sensor signals. The features for the monitoring are selected based on this analysis. At the second work piece the monitoring starts with initial parameters. In parallel to the monitoring task the quality of the monitoring is assessed continuously. Based on this assessment an optimization algorithm searches for a superior setup for the monitoring task. If a proper setup is found it will be used for the monitoring task, starting with the next process. This paper deals with the issue of the feature selection and self-assessment. A single work piece with different cutting processes was designed for testing. Because of that a segmentation of the manufacturing process is necessary [1]. The aim of this segmentation is to choose matching features for each manufacturing process. Assuming that in series production the first processes are not defective, segmentation and feature selection is done by an analysis of these first processes. As sensors, machine control inherent information such as motor torque or axes positions and a three axis acceleration sensor is used. The testing machine is a CTX420l lathe with powered tools.

2. Process segmentation and analysis

The analyzed reference process consists of seven different types of machining. Table 1 lists the processing steps. The aim of the segmentation is to identify the respective types of machining. In this approach a segment means a part of the

Table 1 Machining steps of the used work piece

Cutting processes	Cycles.	Remark
Cylindrical turning	3	Subsequent finishing
Face turning	4	Subsequent finishing
Trepanning	1	Width of Cut 5mm
Slot milling	2	Depth of cut 1mm
Slab milling	4	Full cut, down-, up milling
Drilling	6	Depth 10mm
Circular milling	2	Peripheral milling

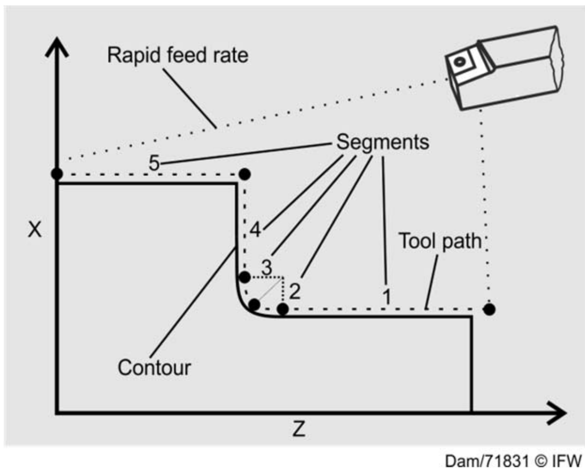

Figure 2 Principle of segmentation

Therefore, similar to the approach of Yohannes [8] a state for each machine axes and spindle is defined. In Table 2 the different states are shown. In combination with the tool ID it is possible to detect areas where no machining is expected, such as positioning with rapid feed rate, tool change or improper trajectories for the actual tool. Given the tool ID of the actual used tool and the axes state it is also possible to determine the process state in the remaining sections. In case of a turning process, for example, there are three possible states: cylindrical turning, face turning or form turning. This distinction is implemented by some sets of logical rules. The first segment starts if the feed velocity is at nominal feed rate. Now a main feed axis is defined. This is the only or fastest feed axis. If the main feed axis or the state of one axis changes a new segment begins. So for each switch between the machining states inside the section of possible machining a new segment is created. Figure 2 shows the principle of the segmentation approach. The first segment starts at the end of rapid feed rate with a constant velocity against z-direction. The second segment starts at the beginning of the curved path where both axes are accelerated. In the middle of the radius the main feed axis changes from the Z-axis to the X-axis. So segment tree starts, which ends with constant feed velocity in x-direction. In the following processes position and velocity are the triggers for the start of a segment. To avoid a false indication each previous segment is checked for a trigger match. The direction of feed motion is known for all segments. The next processing step is to determine a reference feature for each segment.

Table 2 Possible Axes states

Axis/spindle state	Description
0	Hold position
1	Movement with constant velocity
2	Axis is accelerated
3	Movement with rapid speed or tool change position

The major requirement for this selection is the sensitivity to the process state. In most cases this is a dependency to at least one component of the resulting cutting force. This selection is done by an expert system. Based on the tool-ID and the axes states a reference signal is selected. Except milling processes only control inherent signals are used. The aim is to choose a signal source whose signals such as torque or current are influenced as little as possible by disturbances and on the other hand most sensitive to the process condition. Disturbances could be friction, acceleration of the feed axes or random events for example the start of a peripheral device. For machining operations with a rotating tool spindle such as drilling and milling, the tool spindle is selected as reference axes. In most cases the velocity is constant, making it simple to determine the friction part of the torque through a model or an offset, such that only the process part remains. In case of a milling process are features like effective value at tooth engagement frequency from the acceleration sensors also available. That feature with the best signal to noise ratio will be selected if several potential reference features are

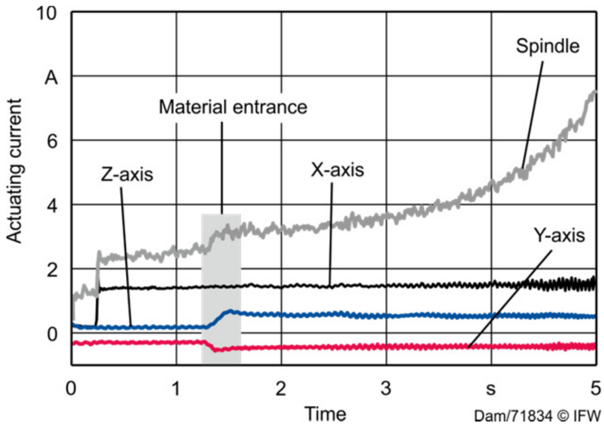

Figure 3 Signal sequences of feed axes and spindle on a face turning process

available. For turning and other processes the preferred reference axis is determined by the following set of rules.

- Workpiece spindle is reference if its state is 1
- Else, main feed axis is reference if its state is 1
- Otherwise the feed axes with state 0 and the best signal to noise ratio is reference

These rules are originated by the attempt to minimize the error by friction and acceleration of feed axes. So axes with constant velocity are preferred to avoid complications at friction compensation at zero velocity [10]. Too confirm the selection of the reference feature an analyses of the process sensitivity is performed. Figure 3 shows the signal sequences on a face turning process. Because of the small-sized depth of cut there is no change in the signal characteristic of the X-axis. This illustrates the need of a confirmation. According to the selection rules the actuating current of the X-axis would be selected as reference feature. However there is no correlation with the cutting process in the signal sequence detectable. To confirm the selection the signal to noise ratio from the friction compensated signals is calculated. In this case the Z-axis would be selected as reference. This approach is also applicable for further machining methods such as keyway slotting. The signal sequence of the reference feature is the basis for the selection of additional features.

2.1. Feature selection

To identify suitable signal features the signal sequence of the reference feature is filtered with a LP-filter. The resulting feature should correlate with at least one component of the cutting force at correct process identification. This is ensured by the prior selection of the reference signal. The reference feature is used to identify additional process sensitive features from the available signal sources. Table 3 lists the signal sources and the analyzed features which are used in an automatic analysis for every generated segment from Table 1. The controller inherent signals are available with a sample time of 12ms and the signals of the three axis acceleration sensor with a sample time of 100µs. The acceleration sensor itself is mounted on the Y-axes close to the turret. For a first selection of available features a covariance analysis with the reference feature is performed for each segment. Features which show the best correlation with the reference feature were compared in a second step. For this purpose a sliding effective value with a cutoff frequency of ten hertz is created from the relevant features. To compare the different features they will be normed to their own noise. This is done by a calculation of the standard deviation with sliding windows. The sliding average of the original signal sequence $\bar{X}$(j) (1) is divided by these sliding standard deviation σ(j) (2). By an additional multiplication with the square root of the window width N the calculated signal sequence meets a statistical test variable for an parameter test if there is an signal greater zero with the critical value c (3). The critical value c can be calculated with a given confidence limit and the inverse student t-distribution.

$$\bar{X}_{(j)} = \frac{1}{N}\sum_{i=0}^{N-1} X(j-i) \tag{1}$$

$$\sigma_{(j)} = \sqrt{\frac{1}{N}\sum_{i=0}^{N-1}\left(\bar{X}_{(j)} - X_{(j)}\right)^2} \tag{2}$$

$$c \geq \frac{\bar{X}_{(j)}-0}{\sigma_{(j)}} * \sqrt[2]{N-1} \tag{3}$$

Parallel to the feature selection based on signal analysis process specific features were selected knowledge based. This includes the signal of the acceleration sensor at tool rotational speed, tooth engagement frequency and the first harmonic in milling processes [1]. In addition the torque of the drive in feed direction in drilling [5] is selected. For both types of features it is assumed that they are sensitive to the process state. The aim is a comparison of features selected by an analysis algorithm and features selected knowledge based. For this comparison the characteristic on real process errors for both kinds of features is performed.

Table 3 Used signal sources and features

Signal source	Features
Torque feed drive X-Y-Z direction	HP/LP Filter, cut off frequency 10Hz, time derivation,
Torque tool/main spindle	HP/LP Filter, cut off frequency 10Hz, time derivation
Three axis acceleration sensor	Effective value for a bandwidth of 250 Hz for a range from 0 to 5kHz for all three directions

2.2. Comparison between analyses and knowledge based Feature selection

A good correlation with the reference feature is given for all selected features. However, it is not possible to deduct the sensitivity of a feature from the signal based selection to the process state. In case of critical tool wear or tool breakage, not all features show the expected behavior. In Figure 4, knowledge based selected features and analyses based features for non-defective- and defective processes are compared for a drilling and a milling process. In case of the drilling process the torque of the tool spindle is the reference

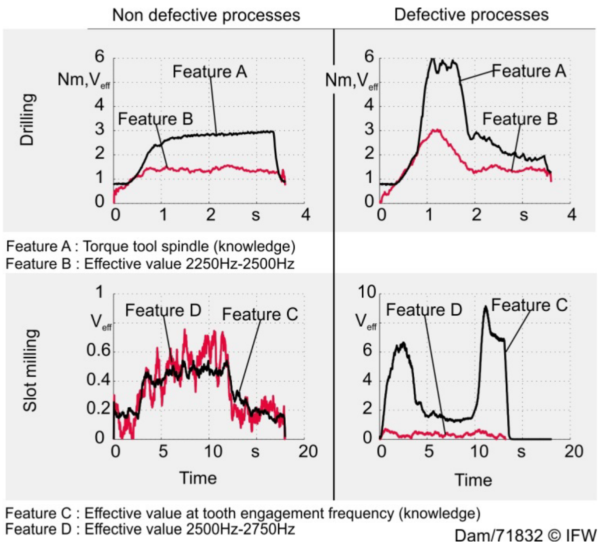

Figure 4 Comparison of automatic selected features

feature. The feature exhibiting the best correlation to the reference feature is the effective value for a specific frequency range from 2250Hz to 2500Hz. In comparison to the non-defective process a change of characteristic is visible in the signal sequences of both features. In case of the slot milling process reference feature is the signal of the acceleration sensor at tooth engagement frequency. The feature with the best correlation is the effective value for a specific frequency range from 2500Hz to 2750Hz. Just like the drilling process the amplitude of both signals, best knowledge based selection and best signal analysis based selection in the non-defective process, is comparable. Hence in the defective process of slot milling in Figure 4 there is no change in the signal characteristic of the feature selected by the signal analyses algorithm. A precise analysis suggests that in cases of drilling and slot milling the cycling frequency of a bearing was selected. In the drilling process through the rising feed force the signal amplitude in this frequency area increases. In the slot milling process the failure has no influence to the selected frequency, because the passive cutting force was not affected by the failure like the feed force on the drilling process. So at the milling process the additional feature selected by the analysis algorithm form the high frequency signals are not suited for process monitoring. For all processes seemingly sensitive features were found. Additional extraction methods were performed to test these features. Overall the analysis of all features and their behavior to process errors shows that the knowledge base selected features seems well suited for process monitoring with the aim to detect critical tool wear or breakage. From the features selected through a signal analysis only a fraction is suitable for monitoring. At high frequency no additional use full features were found by the algorithm. But from the control inherent signals additional use full features were selected. In most cases the algorithm detects the knowledge based features to. A distinction between proper and improper features without analyses of their behavior in case of a process error was not possible at this state.

3. Assessment of monitoring quality

Independent from the feature selection it is analyzed in which extend it is possible to assess the quality of the monitoring of a single feature monitoring. Main requirement to the used features is a change of characteristic in case of a process error. According to the specific application disturbances in the signals of the feed drives such as friction, acceleration or latching forces have to be compensated by suitable methods [9 e.g.]. For the assessment of monitoring quality two characteristics were evaluated: The gap between the long term average and its threshold as well as the time behavior of the

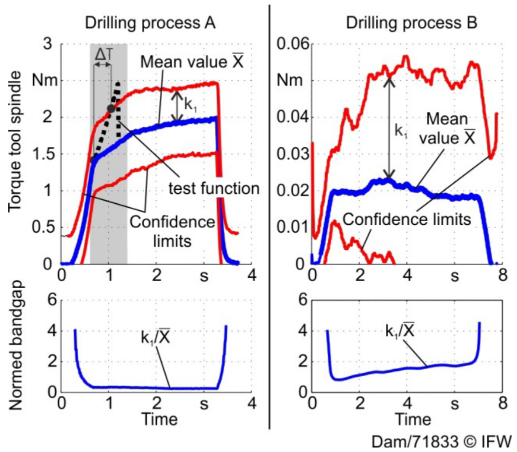

Figure 5 Feature evaluation

monitoring to real process errors and test functions. According to the variation coefficient (relative standard deviation, ratio from standard deviation to average) the distance k between average $\bar{X}$ and its threshold λ_u is normalized to the average (4).

$$Vk = \frac{k}{\bar{X}} = \frac{\lambda_u - \bar{X}}{\bar{X}} \tag{4}$$

This characteristic indicates in which range the normed feature must change to cause an alarm. If statistical thresholds are used, the gap between average and threshold is given by a fixed confidence belt which is equivalent to the probability of a false alarm [6]. For other monitoring methods with threshold it is possible to calculate the probability of a false alarm by the student's t-distribution. Therefore a confidence limit based on the distribution of the signal around its long-term average is calculated. To estimate the performance of the monitoring system without real process errors test functions were used. These functions are meant to represent the signal characteristic in case of two types of process errors: Tool breakage is approximated by a short impulse with 10ms duration (1). Sudden tool failure resulting from too high cutting temperature for example is represented by a ramp with duration of 500ms (2). Both functions are scaled with a factor α. As suitable values for the factor α values between 1,5 to 2 have been proven. Thereby the aim is to represent sudden tool failure and breakage not gradually tool wear. To determine the reaction time of the monitoring system the original signal is multiplied with both test functions. The time lag between start of the test function and crossing of the threshold is the estimated reaction time. (Figure 4)

$$f_{1(T_0+t)} = \begin{bmatrix} 1: t = 0 \\ \alpha: t \le 10ms \\ 0: t > 10ms \end{bmatrix} \tag{5}$$

$$f_{2(T_0+t)} = \begin{bmatrix} 1: t = \ 0 \\ 1 + (\alpha - 1) \times \frac{t}{500ms}: t \le 500ms \\ \alpha: t > 500ms \end{bmatrix} \tag{6}$$

Thereby a time window of 500ms will be observed. The three characteristics, estimated reaction time, probability of a false alarm and band gap are no absolute scale for the fitness of a single feature monitoring, but at means of comparing different features, identify improper features and difficult to monitor process segments. Figure 5 shows a comparison of two drilling processes. For both processes a confidence belt of five standard deviations was applied. In the first drilling process the normed band gap of about 0,5 during process indicates a good monitoring ability. In the second drilling process a normed band gap of about 1 to 2 indicates that an increase of the amplitude to 300% is necessary to affect an alarm. To evaluate the significance of the referred characteristics their values were compared to the behavior of the assessed features to real process errors. Table 4 lists the results for an assessment of the monitoring features for a drilling process. Evaluation criterions are the normed band gap, estimated reaction time and confidence belt. The parameters for the feature extraction were set by a genetic algorithm to optimize the monitoring setup for a multi criteria monitoring.

Table 4 Assessment of features for a drilling process with test function

Signal source	Feature & gap assessment	Test function	Confidence belt	Estimated reaction time
Torque tool spindle	LP 0,45	Impulse	0,99997	24ms
	LP 0,45	Ramp	0,99997	312ms
	Time derivation 1,198	Impulse	0,95	12ms
	Time derivation 1,198	Ramp	0,95	Not detected
Torque feed drive	LP 0,44	Impulse	0,99993	36ms
	LP 0,44	Ramp	0,99993	336ms

In case of the impulse test function at all three features the threshold was exceeded immediately. Depending on its extraction method the time derivation is not able to detect the second test function. This prediction is confirmed by the behavior to real process errors occurred at tool wear tests. For the used features it is possible to make a statement about their monitor-ability. Because of the complex relations in cutting processes and the large number of types of tool wear and tool failure a certain statement about the sensitivity of a feature to the process condition is only possible with process data of real process errors with this approach. Table 5 shows the reaction time of the same three features with identical monitoring boarders to a tool failure. The tool failure occurs allocated on four drilling processes. The first defect process is the first where a limit overstepping occurs. On the fourth process the tool breaks finally. The first three errors can be compared with the ramp test function. The fourth with the step test function. Because it is not possible to define a start time for the errors the reaction times are given relative to the detection at the low pass filtered spindle torque. In the case of the reaction to an abruptly change the behaviour on real errors is similar to the test functions. Not as expected is the behaviour of the last feature, the low pass filtered feed torque. Maybe the tool behaviour in case of the occurred failure is causal therefore.

Table 5 Reaction time to real process errors

Signal source	Feature & gap assessment	Relative reaction time			
		Error 1	Error 2	Error 3	Error 4
Torque tool spindle	LP 0,45	0 ms	0 ms	0 ms	0 ms
Torque tool spindle	Time derivation 1,198	Not detected	Not detected	+ 1740 m s	-48 ms
Torque feed drive	LP 0,44	Not detected	Not detected	+ 1260 m s	+36 ms

4. Conclusion and outlook

It was shown that it is possible to realize an autonomous process segmentation and feature selection based on the automatic analysis of manufacturing processes. Considering the results it becomes clear that a secure selection is only possible with knowledge based approach. At the low frequency control inherent signals use full additional features were selected by the presented algorithm. At the high frequency external sensors both, use full and useless features were selected. Thus an added value results only for low frequency signal sources through the analysis based algorithm. During the test procedure in some cases for monitoring, suitable features were only determined by selection rules. Features selected based on the signal analysis were not all sensitive for process errors. Limiting factor for the monitoring is the signal-to-noise ratio. The ability to select signals with very low amplitude, but a high sensitivity is a second advantage of the knowledge based feature selection. Still, features selected by the analysis algorithm are potential sensitive to the process state. But a certain assessment is only possible after an error occurred. Therefore it seems to be reasonable to make a reassessment of the features, having real error data. In addition an approach for a self-assessment based on statistical analysis and test function was shown. The test functions approximate two types of process errors. The self-assessment of the single feature monitoring can be used as an indicator for a proper monitoring and a scale for a comparison of different monitoring approaches. Finally the complete approach of a self-parameterizing monitoring system will be evaluated with an online demonstrator.

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